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Optimal scheduling for energy harvesting mobile sensing devices

Weiwei Fang [a,b,*], Xiaojie Zhao [a], Yuan An [b], Jing Li [b], Zhulin An [c], Qiang Liu [a]

[a] School of Computer and Information Technology, Beijing Jiaotong University, Beijing 100044, China
[b] State Key Lab of Astronautical Dynamics of China, Xi'an 710043, China
[c] Institute of Computing Technology, Chinese Academy of Sciences, Beijing 100190, China

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ABSTRACT

The rapid advances in mobile devices and their embedded sensors have enabled a compelling paradigm for collecting ubiquitous data to share with each other or the general public. In this paper, we study how to achieve the close-to-optimal transmission utility performance for sensor-enhanced mobile devices that are capable of harvesting energy from the environment. This is a very challenging task due to the stochastic and unpredictable nature of data arrival, channel condition, and energy replenishment. By taking advantage of the Lyapunov optimization framework, we propose an online scheduling algorithm called OSCAR (Optimal SCheduling AlgoRithm), which jointly make control decisions on system state, energy harvesting, and data transmission for achieving optimal utility on mobile sensing devices. Different from traditional techniques, OSCAR does not require any knowledge of system statistics, including the energy state process. Rigorous analysis and extensive experiments have demonstrated both the system stability and the utility optimality achieved by the OSCAR algorithm.

1. Introduction

Recent advances in mobile devices (e.g., smartphones, wearable devices and sensor-equipped vehicles) and their embedded sensors (e.g., camera, microphone and GPS) have provided a novel paradigm for sensing and monitoring human daily behaviors [1], urban environment [2], and even earth surface [3]. Data information collected by these mobile devices combined with the support of the cloud where data fusion takes place [4], make mobile sensing a versatile platform to relieve the need for deploying and maintaining static sensing infrastructures. However, the advances in battery have been slow to respond to mobile application demands evolved over the years. Energy-harvesting, i.e., converting ambient energy to electricity energy, has emerged as an alternative to address the problem of finite battery capacity [5]. To take full advantage of the energy harvesting capacity, it is of central importance to develop energy management algorithms for mobile sensing devices to improve communication performance and energy efficiency [6].

In this paper, we consider the problem of designing an utility optimal scheduling algorithm for a single sensor-enhanced mobile device system. The system operates in discrete time with unit time slots. In every time slot, the first decision for the device to make is to decide whether to enter the sleep state or stay active during this slot. If it enters the sleep state, it turns off the network module and does not respond to any task request for processing or transmitting data. If instead the device stays active, then it determines how much sensory data to admit for the flows it supports, and how to use current network and energy resources efficiently for data transmission. The system receives utility by transmitting sensory data to a dedicated server that is responsible for data storage and analysis [7]. Our objective is to maximize the aggregate flow utility, subject to the constraints that the average data backlog is finite, and the energy consumed is no more than the energy stored at all time. The constraint on energy availability obviously complicates the design of scheduling algorithm, since the current control decisions may cause energy outage in the future and affect some future control decisions [7]. Such a problem can be modelled and solved by Dynamic Programming [8]. However, the Dynamic Programming approach requires substantial statistical information of the system dynamics, and suffers from the "curse of dimensionality" where the complexity of computing the optimal strategy grows with the system size [8].

To address the above problem, we propose an Optimal SCheduling AlgoRithm (OSCAR) for achieving optimal utility for sensor-enhanced mobile devices with energy harvesting capabilities, based on the recently developed technique of Lyapunov optimization [8]. OSCAR maximizes the traffic utility by independently and simultaneously making online decisions to control system state, energy harvesting and data transmission behaviors. It is able to obtain a time average utility within a deviation of $\mathcal{O}(1/V)$ from the optimum, with an

* Corresponding author. Tel.: +86 10 51688536.
E-mail addresses: wwfang@bjtu.edu.cn, fangvv@gmail.com (W. Fang), 14125221@bjtu.edu.cn (X. Zhao), yanadl@gmail.com (Y. An), jliadl@gmail.com (J. Li), anzhulin@ict.ac.cn (Z. An), liuq@bjtu.edu.cn (Q. Liu).

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average queue size tradeoff that is $\mathcal{O}(V)$, where V is a non-negative parameter that weights the extent to which utility maximization is emphasized as compared to system stability. OSCAR operates without requiring any statistical knowledge of system dynamics, and is computationally efficient for implementation. We thoroughly evaluate the performance of OSCAR with rigorous theoretical analysis and extensive simulation experiments.

The remainder of this paper is organized as follows. In Section 2, we present the problem formulation, and in Section 3, we develop our online algorithm, OSCAR, as well as provide its performance analysis. The analysis is further validated by extensive simulation experiments introduced in Section 4. Section 5 reviews some related studies. Finally, Section 6 concludes this paper.

2. Problem formulation

We consider a system consists of a single mobile sensing device, which has been equipped with M types of sensors [9]. This device is powered by a finite capacity battery, and is capable of harnessing energy from the environment and converting it to electrical energy [5,10]. Due to inherent resource constraints, the device has to transfer the sensory data to a dedicated server for storage, analysis and making them available to interested people [4,11]. The whole system operates in discrete time with unit time slots $t \in \{0, 1, 2, \ldots\}$.

2.1. Device working state model

In each time slot t, the device can choose to stay in the active state or in the sleep state, so as to better utilize the harvested and stored energy. We model this active/sleep decision by $\theta(t)$. That is, $\theta(t) = 1$ if the device transmits data in time slot t, otherwise $\theta(t) = 0$.

2.2. Data transmission utility model

In time slots when the device stays active, it decides how much sensory data generated from its sensor $m \in \{1, \ldots, M\}$ can be admitted into the transmission buffer for further handling. These data are classified and stored in separate queues according to their types. Let $R_m(t)$ represents the amount of type m data queued at time t. We assume that $0 \le R_m(t) \le R_{max}$ for all $m \in \{1, \ldots, M\}$ with some finite constant R_{max} at all time. During time slots when the device is in the sleep state (i.e., $\theta(t) = 0$), we have $R_m(t) = 0$ for all $m \in \{1, \ldots, M\}$.

Each type of sensory data is associated with a utility function $\Lambda_m(\bar{r}_m)$, where $\bar{r}_m$ is the time average rate of the type m sensory data admitted into the buffer, defined as $\bar{r}_m = \lim_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} \mathbb{E}\{\theta(t)R_m(t)\}$. Each function $\Lambda_m(r)$ is assumed to be non-decreasing, continuously differentiable, and strictly concave in r with a bounded first derivative [7]. Besides, $\Lambda_m(0) = 0$. We use λ_m to denote the maximum first derivative of $\Lambda_m(r)$, i.e., $\lambda_m = (\Lambda_m)'(0)$ and denote

$$\lambda = \max_m \lambda_m \tag{1}$$

2.3. Transmission energy consumption model

We assume that the device has been equipped with more than one wireless interfaces, e.g., Bluetooth, WiFi or 3G [12,13], that are heterogeneous in terms of network availability, achievable throughput and energy expenditure [11,14]. If the device stays active in a time slot, its network module needs to choose a suitable one from available wireless links for transmitting data to the server [11,15]. Let $\omega(t)$ denotes this transmission decision, and the vector of data service rates [8] $\mu(t) = (\mu_1(t), \ldots, \mu_M(t))$ is jointly determined by $\omega(t)$ and channel state $S(t)$. Specifically, the network module observes the current $S(t)$ and selects $\omega(t)$ within some abstract set Ω that specifies the decision options. Then, the service rates for slot t can be given by functions $\hat{\mu}_m(\omega, S)$ as $\mu_m(t) = \hat{\mu}_m(\omega(t), S(t))$ for each $m \in \{1, \ldots, M\}$. We assume a maximum transmission rate μ_m^{max}, regardless of $\omega(t)$ and $S(t)$, so that $0 \le \hat{\mu}_m(\omega(t), S(t)) \le \mu_m^{max}$.

It has been revealed by recent studies [14] that, the amount of energy consumed for data transmission by a mobile device is primarily associated with the wireless interface used and its current link bandwidth, as formally characterized as follows:

$$N(t) = [\alpha B(t) + \beta]\tau \tag{2}$$

where α and β denote the empirical coefficients in the power model, and different types of interfaces have distinct power coefficients [14]. Besides, τ denotes the time span of one time slot, and $B(t) = \hat{B}(\omega(t), S(t))$ is the bandwidth of current selected link in time slot t. It is obvious that there exists the constraint that $N_{min} \le N(t) \le N_{max}$ for some $0 < N_{min} < N_{max} < \infty$. Since the system bandwidth is shared by all the M types of data flows, we know that $B(t)\tau = \sum_{m=1}^{M} \mu_m(t)$.

2.4. Energy queue model

The device is assumed to be powered by a battery with a finite capacity. We use $E(t)$ to denote the amount of remaining energy left in the battery observed by the device at time t. It is compulsory that the consumed energy must be no more than what is available. Therefore, the energy consumption actions have to satisfy the following constraint:

$$P(t) + N(t) \le E(t) \tag{3}$$

where $P(t)$ denotes the energy consumed for state transition, data processing and system management. We assume that $P(t)$ is known to the device [15,16], and $0 \le P(t) \le P_{max}$ with some finite P_{max} for all time. Actually, for some mobile devices featured by low power and long lifetime, this portion of energy consumption can even be neglected (i.e., $P(t) \approx 0$) as compared with that for data transmission [9,17].

The device is assumed to be capable of harnessing energy from the environment and converting it to electrical energy. The energy harvested in time slot t is assumed to be available for use in the next time slot $t + 1$. However, the amount of harvestable energy in a time slot is typically unpredictable and varies over time. To model this dynamic nature, we use $h(t)$ to denote the amount of harvestable energy at time t. We also assume that $h(t)$ takes values from some finite set $\mathcal{H}$, and $0 \le h(t) \le h_{max}$ where h_{max} is dependent on environmental factors for a given battery [5,7]. The device is able to make a decision on energy harvesting by choosing $e(t) \in [0, h(t)]$, where $e(t)$ denotes the amount of energy that is actually harvested at time t.

2.5. Queue dynamics

Let $\mathbf{Q}(t) = (Q_m(t), m \in \{1, \ldots, M\})$ be the data queue backlog vector in the device, where $Q_m(t)$ is the amount of type m sensory data queued at the device in time slot t. We can capture the following queueing dynamics of the device:

$$Q_m(t+1) = \max[Q_m(t) - \theta(t)\mu_m(t), 0] + \theta(t)R_m(t) \tag{4}$$

where $Q_m(0) = 0$ for all $m \in \{1, \ldots, M\}$. Accordingly, we can define the stability constraint on the queues, which ensures that the average queue length is finite. The queue stability can be defined as follows:

$$\bar{Q} \triangleq \lim_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \sum_{m=1}^{M} \mathbb{E}\{Q_m(t)\} < \infty \tag{5}$$

Similarly, $E(t)$ denotes the energy queue size. Due to the constraint on energy availability (3), the energy queue $E(t)$ evolves according to the following:

$$E(t+1) = E(t) - \theta(t)[P(t) + N(t)] + e(t) \tag{6}$$

We will show that under our OSCAR algorithm, the energy level $E(t)$ is deterministically upper-bounded, which is desirable for practical implementations.

2.6. Optimization objective

The goal of OSCAR is to design a joint system state, energy harvesting, and data transmission algorithm that at every time slot makes the right sleep/active decision $\theta(t)$, admits the right amount of data $R_m(t)$, chooses the suitable wireless interface (i.e., $\omega(t)$) subject to (3), and then transmits packets accordingly, so as to solve the following optimization problem subject to the constraint on system stability (5):

$$\max f(\bar{\mathbf{r}}) = \sum_{m=1}^{M} \Lambda_m(\bar{r}_m) \tag{7}$$

where $\bar{\mathbf{r}} = (\bar{r}_m, m \in \{1, \ldots, M\})$ denotes the vector of the time average expected admitted rates.

3. Algorithm design

In this section, we propose the Optimal SCheduling AlgoRithm (OSCAR) algorithm designed following the Lyapunov optimization framework, as developed in [8], to solve the optimization problem (7). In particular, OSCAR is designed to solve problem (7) with close-to-optimal performance by using Lyapunov optimization with weight perturbation. The technique of weight perturbation, as proposed in [7], is used to ensure that the energy queue $E(t)$ is kept close to a target value to avoid battery underflow.

Specifically, we choose a perturbation value ϕ and define the Lyapunov function as follows:

$$L(t) \triangleq \frac{1}{2}\sum_{m=1}^{M}[Q_m(t)]^2 + \frac{1}{2}[E(t) - \phi]^2 \tag{8}$$

The design parameter ϕ is used to avoid battery underflow, and to ensure that the energy queue always have enough energy when the device is active and working. We will show that with a proper choice of ϕ, the energy level of device battery is guaranteed to be such that constraint (3) is never violated.

Then, we denote $\mathbf{\Theta}(t) = (\mathbf{Q}(t), E(t))$ and define a one-slot conditional Lyapunov drift as follows:

$$\Delta(\mathbf{\Theta}(t)) \triangleq \mathbb{E}[L(\mathbf{\Theta}(t+1)) - L(\mathbf{\Theta}(t))|\mathbf{\Theta}(t)] \tag{9}$$

Here, the expectation is taken over the randomness of data arrival, channel condition and energy replenishment, as well as the randomness in choosing the control actions. If control decisions are made in every time slot t to greedily minimize $\Delta(\mathbf{\Theta}(t))$, then all queue backlogs are consistently pushed towards a lower congestion state, which intuitively maintains system stability [8]. However, the objective utility function in (7) should also be incorporated. Thus, following the Lyapunov optimization framework, we add a function of the expected utility function over one period (i.e., the penalty function) to obtain the following drift-plus-penalty term:

$$\Delta_V(\mathbf{\Theta}(t)) \triangleq \Delta(\mathbf{\Theta}(t)) - V\mathbb{E}\left\{\sum_{m=1}^{M}\Lambda_m(\theta(t)R_m(t))|\mathbf{\Theta}(t)\right\} \tag{10}$$

where $V \geq 0$ is a parameter set by system operators to control the tradeoff between utility maximization (i.e., problem (7)) and system stability. Note that the sign of the penalty expression in (10) is negative, since we need to transform the maximization problem (7) into an equivalent one of penalty minimization in Lyapunov optimization [8,11].

We have the following lemma regarding the drift-plus-penalty term:

Lemma 1. *Under any feasible action that can be implemented in time slot t, we have:*

$$\begin{aligned}\Delta_V(\mathbf{\Theta}(t)) \leq\ & B + \mathbb{E}\{(E(t)-\phi)e(t)|\mathbf{\Theta}(t)\} \\ & - \mathbb{E}\left\{\sum_{m=1}^{M}[V\Lambda_m(\theta(t)R_m(t)) - Q_m(t)\theta(t)R_m(t)]|\mathbf{\Theta}(t)\right\} \\ & - \mathbb{E}\left\{\sum_{m=1}^{M}Q_m(t)\theta(t)\mu_m(t) + (E(t)-\phi)\theta(t)N(t)|\mathbf{\Theta}(t)\right\} \\ & - \mathbb{E}\{(E(t)-\phi)\theta(t)P(t)|\mathbf{\Theta}(t)\}\end{aligned} \tag{11}$$

where $B \triangleq \frac{1}{2}[MR_{max}^2 + \sum_{m=1}^{M}(\mu_m^{max})^2 + (P_{max} + N_{max})^2 + h_{max}^2]$.

Proof. First by squaring both sides of (4), summing over $m \in \{1, \ldots, M\}$, and by using the fact that for any $Q \geq 0$, $b \geq 0$, $A \geq 0$, $(max[Q-b, 0] + A)^2 \leq Q^2 + A^2 + b^2 + 2Q(A-b)$, we have:

$$\begin{aligned}\frac{1}{2}\sum_{m=1}^{M}([Q_m(t+1)]^2 - [Q_m(t)]^2) \leq\ & \frac{1}{2}\sum_{m=1}^{M}([R_m(t)]^2 + [\mu_m(t)]^2) \\ & -\theta(t)\sum_{m=1}^{M}Q_m(t)[\mu_m(t) - R_m(t)]\end{aligned} \tag{12}$$

Using a similar approach, we get that:

$$\begin{aligned}\frac{1}{2}([E(t+1)-\phi]^2 - [E(t)-\phi]^2) \leq\ & \frac{1}{2}[P(t)+N(t)]^2 \\ & + \frac{1}{2}[e(t)]^2 - (E(t)-\phi)[\theta(t)(P(t)+N(t)) - e(t)]\end{aligned} \tag{13}$$

Then, by summing (12) and (13), and by defining $B \triangleq \frac{1}{2}[MR_{max}^2 + \sum_{m=1}^{M}(\mu_m^{max})^2 + (P_{max} + N_{max})^2 + h_{max}^2]$, we have:

$$\begin{aligned}L(t+1) - L(t) \leq\ & B - \theta(t)\sum_{m=1}^{M}Q_m(t)[\mu_m(t) - R_m(t)] \\ & -(E(t)-\phi)[\theta(t)(P(t)+N(t)) - e(t)]\end{aligned} \tag{14}$$

Taking expectations on both sides over the system dynamics and the randomness over actions conditioning on $\mathbf{\Theta}(t)$, subtracting from both sides the term $V\mathbb{E}\{\sum_{m=1}^{M}\Lambda_m(\theta(t)R_m(t))\}$, and rearranging the terms, we can see that the lemma follows. □

Hence, rather than directly minimize the drift-plus-penalty expression in each time slot, we can actually seek to minimize the bound given in the right-hand-side of (11). In our algorithm presentation, we use the following metric for determining the sleep/active decision in each time slot:

$$\begin{aligned}A(t) \triangleq\ & \sum_{m=1}^{M}[V\Lambda_m(R_m(t)) - Q_m(t)R_m(t)] \\ & + \sum_{m=1}^{M}Q_m(t)\mu_m(t) + (E(t)-\phi)N(t) + (E(t)-\phi)P(t)\end{aligned} \tag{15}$$

Optimal SCheduling AlgoRithm (OSCAR): Initialize ϕ. In each time slot t, perform the following actions:

- *Sleep/Active scheduling*: Observe $\mathbf{Q}(t)$, $E(t)$, $S(t)$ and $P(t)$, solve:

$$\begin{aligned} \max:\ & \mathbb{E}\{A(t)\} \\ s.t.\ & 0 \le R_m(t) \le R_{max}, \omega(t) \in \Omega \end{aligned} \tag{16}$$

Denote the optimal solution by A^*. Then, if $A^* < 0$, the device sets $\theta(t) = 0$, and enters the sleep state. Otherwise, it enters the active state, i.e., $\theta(t) = 1$. If the device enters the sleep state, it sets $R_m(t) = 0$ for all $m \in \{1, \ldots, M\}$ and stops data transmission. Else if it enters the active state, it performs the following actions for data admission and interface selection in the same time slot t to maximize (15):

  - *Data admission*: Choose $R_m(t)$ to be the optimal solution of the following optimization problem:

$$\begin{aligned} \max:\ & V\Lambda_m(R_m(t)) - Q_m(t)R_m(t) \\ s.t.\ & 0 \le R_m(t) \le R_{max} \end{aligned} \tag{17}$$

  - *Interface selection*: Choose one from current available interfaces [11,15] to be the optimal solution of the following optimization problem:

$$\begin{aligned} \max:\ & \textstyle\sum_{m=1}^{M} Q_m(t)\hat{\mu}_m(\omega(t), S(t)) \\ & + (E(t) - \phi)[\alpha\hat{B}(\omega(t), S(t)) + \beta]\tau \\ s.t.\ & \omega(t) \in \Omega \end{aligned} \tag{18}$$

- *Energy harvesting*: If $E(t) - \phi < 0$, perform energy harvesting and store the harvested energy, i.e., $e(t) = h(t)$. Otherwise, set $e(t) = 0$. Note that this decision is to minimize the $\mathbb{E}\{(E(t) - \phi)e(t)|\mathbf{\Theta}(t)\}$ term in (11).
- *Queue update*: Update $Q_m(t)$ and $E(t)$ according to (4) and (6), respectively.

The time complexity for the OSCAR algorithm is $\mathcal{O}(M)$. From the energy harvesting step of OSCAR, we know that the device will harvest energy only when the energy level is lower than ϕ, and therefore $E(t) \le \phi + h_{max}$ for all t. This is an important feature because it allows to implement OSCAR using a battery providing energy with finite capacity size of $\phi + h_{max}$.

Theorem 1. *Under the OSCAR algorithm, we have the following:*

(a) The data queues and the energy queue satisfy the following for all time slots:

$$0 \le Q_m(t) \le \lambda V + R_{max} \tag{19}$$

$$0 \le E(t) \le \phi + h_{max} \tag{20}$$

(b) Define the parameter ϕ as:

$$\phi \triangleq \frac{MVR_{max}\lambda + (V\lambda + R_{max})\mu_{max}}{N_{min}} + (P_{max} + N_{max}) \tag{21}$$

then in any time slot t, if the device enters the active state, we must have $E(t) \ge P_{max} + N_{max}$.

(c) With the same definition of ϕ in part (b), we have:

$$f(\bar{\mathbf{r}}) \ge f^* - \frac{B}{V} \tag{22}$$

where f^* is the optimal time average utility function of our problem.

Proof.

(a) It is easy to see that (19) holds for $t = 0$ since $Q_m(t) = 0$ for all $m \in 1, \ldots, M$. Suppose this is true for a particular time slot t. We show it also holds for $t + 1$. If $0 \le Q_m(t) \le \lambda V$, then $Q_m(t+1) \le \lambda V + R_{max}$, because $Q_m(t)$ can increase by at most R_{max}. If $\lambda V \le Q_m(t) \le \lambda V + R_{max}$, and we know that $\Lambda_m(R_m(t)) < \lambda R_m(t)$ from the definition of $\Lambda_m(t)$ and λ, then the data admission decision will choose $R_m(t) = 0$ according to (17). Thus, the queue $Q_m(t)$ can not increase in the next time slot, and we have $Q_m(t+1) = Q_m(t) \le \lambda V + R_{max}$. This proves (19).
Similarly, it is easy to see from the energy harvesting decision that whenever $E(t) > \phi$, OSCAR will choose $e(t) = 0$, which proves (20).

(b) We first show that whenever $E(t) < P_{max} + N_{max}$, OSCAR will put the node into the sleep state. This claim will allow us to compare our algorithm with alternative algorithms that make control decisions without taking the energy constraint (3) into consideration. To prove this claim, consider a given time slot t and assume that $E(t) < P_{max} + N_{max}$. Let $R_m^*(t)$, $\mu_m^*(t) = \hat{\mu}_m(\omega^*(t), S(t))$, and $N^*(t) = [\alpha\hat{B}(\omega^*(t), S(t))]\tau$ be the optimal solution of (15) for the given $E(t)$ and $Q_m(t)$. Then, using (1), (19), $\Lambda_m(R_m(t)) < \lambda R_m(t)$, and $N_{min} \le N(t) \le N_{max}$, we have:

$$\begin{aligned} A(t) \le\ & \sum_{m=1}^{M}[V\Lambda_m(R_m^*(t)) - Q_m(t)R_m^*(t)] \\ & + \sum_{m=1}^{M} Q_m(t)\mu_m^*(t) + (E(t)-\phi)N^*(t) + (E(t)-\phi)P(t) \\ \le\ & MVR_{max}\lambda + (V\lambda + R_{max})\mu_{max} \\ & + (P_{max} + N_{max} - \phi)(N^*(t) + P(t)) \\ \le\ & MVR_{max}\lambda + (V\lambda + R_{max})\mu_{max} \\ & - \frac{MVR_{max}\lambda + (V\lambda + R_{max})\mu_{max}}{N_{min}}(N^*(t) + P(t)) \le 0 \end{aligned} \tag{23}$$

Therefore, the device will enter the sleep state according to the sleep/active scheduling rule of OSCAR. Though OSCAR explicitly considers the constraint (3), it remains the same if this redundant constraint is removed as long as ϕ is defined as equal to or larger than that in (21). The right-hand-side of the inequality (11) can be minimized without considering the energy constraint (3)

(c) We now use π to denote any alternative (possibly randomized) policy other than the optimal one. According to Theorem 4.8 in [8] and part (b), the resulting values of $\theta^\pi(t)$, $R_m^\pi(t)$, $\mu_m^\pi(t) = \hat{\mu}_m(\omega^\pi(t), S(t))$, and $N^\pi(t) = [\alpha\hat{B}(\omega^\pi(t), S(t))]\tau$ are independent of the current queue backlogs $\mathbf{\Theta}(t)$. According to Caratheodory's theorem [8,18], there exists a $\eta > 0$ such that

$$\begin{aligned} & \mathbb{E}\left\{\sum_{m=1}^{M}\Lambda_m(\theta^\pi(t)R_m^\pi(t))|\mathbf{\Theta}(t)\right\} \\ & = \mathbb{E}\left\{\sum_{m=1}^{M}\Lambda_m(\theta^\pi(t)R_m^\pi(t))\right\} = f^* + \eta \end{aligned} \tag{24}$$

$$\begin{aligned} & \mathbb{E}\left\{\theta^\pi(t)\sum_{m=1}^{M}[\mu_m^\pi(t) - R_m^\pi(t)]|\mathbf{\Theta}(t)\right\} \\ & = \mathbb{E}\left\{\theta^\pi(t)\sum_{m=1}^{M}[\mu_m^\pi(t) - R_m^\pi(t)]\right\} = \eta \end{aligned} \tag{25}$$

$$\begin{aligned} & \mathbb{E}\{\theta^\pi(t)(P(t) + N^\pi(t)) - e(t)|\mathbf{\Theta}(t)\} \\ & = \mathbb{E}\{\theta^\pi(t)(P(t) + N^\pi(t)) - e(t)\} = \eta \end{aligned} \tag{26}$$

Table 1
Power parameters for different wireless interfaces.

	α (mW/Mbps)	β (mW)
WiFi	283.17	132.86
3G	868.98	817.88

Plugging the above (24)–(26) into the right-hand-side of (11) and taking $\eta \to 0$ yields:

$$\Delta(\mathbf{\Theta}(t)) - V\mathbb{E}\left\{\sum_{m=1}^{M}\Lambda_m(\theta(t)R_m(t))|\mathbf{\Theta}(t)\right\} \leq B - Vf^*$$

Taking expectations over $\mathbf{\Theta}(t)$ on both sides, and summing the resulting telescoping series over $t \in \{0, \ldots, T-1\}$ yields:

$$\mathbb{E}\{L(T) - L(0)\} - V\sum_{t=0}^{T-1}\mathbb{E}\left\{\sum_{m=1}^{M}\Lambda_m(\theta(t)R_m(t))\right\} \leq BT - VTf^*$$

Using the fact that $L(T) \geq 0$ and $L(0) = 0$, and rearranging the terms yields:

$$\frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}\left\{\sum_{m=1}^{M}\Lambda_m(\theta(t)R_m(t))\right\} \geq f^* - \frac{B}{V}$$

Taking a limit as $T \to \infty$, and using Jensen's inequality [8,11], we conclude that:

$$f(\bar{\mathbf{r}}) = \sum_{m=1}^{M}\Lambda_m\left(\lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}\{\theta(t)R_m(t)\}\right)$$
$$\geq \lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}\left\{\sum_{m=1}^{M}\Lambda_m(\theta(t)R_m(t))\right\} \geq f^* - \frac{B}{V}$$

This completes the proof of part (c). □

Theorem 1 demonstrates the $[\mathcal{O}(1/V), \mathcal{O}(V)]$ utility-backlog tradeoff for the problem (7). Meanwhile, (20) and (21) imply that the size of energy queue is upper bounded by $\mathcal{O}(V)$. These results provide explicit characterizations of the size of system queues needed for achieving the desired utility performance.

4. Simulation results

In this section, we provide further insights into the performance of OSCAR, via some simulation results. We consider a mobile sensing device equipped with a set of $m = 3$ types of sensors, and two wireless interfaces (WiFi and 3G [12,13]), i.e., $\Omega = \{\text{WiFi, 3G}\}$. The bandwidth traces we use in the simulations are the UMICH measurement datasets from 4G Test Project [14]. The parameters for energy consumption of wireless interfaces are listed in Table 1. According to empirical studies in [11,15], we set the length of one time slot $\tau = 60$ s (A portion of two hour bandwidth variation for the two interfaces is shown in Fig. 1), and we also set $R \in [0, 20]$ and $R_{max} = 20$Mb [15]. Besides, $h(t)$ is a Bernoulli random variable [7], which takes value 20 joules with probability 0.5 and 0 otherwise. For all $m = \{0, 1, 2\}$, the utility function is defined as $\Lambda_m(x) = log(1 + \lambda_m x)$, where $\lambda_m = 5$ [7,8]. The portion of energy consumption P is neglected [9,17], i.e., $P(t) = 0$ for all t.

In the first set of experiments, we fix $T = 10000$ time slots, and then run simulation experiments with different V values. We compare OSCAR with an intuitive algorithm "Fastest", which always tries to admit the maximum amount (i.e., R_{max}) of data and select the interface currently providing the highest bandwidth [11]. Note that the Fastest algorithm has nothing to do with the control parameter V defined in OSCAR. According to Theorem 2.4 in [8], we use a simple admission policy to enforce that $R_m(t) = 0$ when $\bar{r}_m$ is larger than the time average of $\mu_m(t)$, so as to guarantee the rate stability of data queue Q_m. Besides, we use the same rule and setting for energy harvesting as those in OSCAR. The corresponding results are plotted in Fig. 2. We can see that as the V parameter increases from 20 to 500, the time-average utility achieved by OSCAR increases from 5.74 and converges to 10.55 (Fig. 2(a)). Note that the utility grows quickly at the beginning, and then tends to ascend slowly. Meanwhile, both the average data queue size and the average energy level grow linearly in V (Fig. 2(b) and (c)). This quantitatively confirms Theorem 1 that OSCAR achieves an $[\mathcal{O}(1/V), \mathcal{O}(V)]$ utility-backlog tradeoff for our problem, and the energy queue size is deterministically upper bounded by a constant of size $\mathcal{O}(V)$. On the other hand, the Fastest algorithm admits and transmits data aggressively without taking energy consumption and sleep/awake scheduling into consideration. To satisfy the energy availability constraint, the device has to switch more frequently between the awake and the sleep state, while in the sleep state it can neither admit nor transmit data. Such discoordination between data processing and energy state definitely has a significant negative impact on the system throughput. As a result, Fastest is not capable of achieving the optimal utility as OSCAR does when V is large enough.

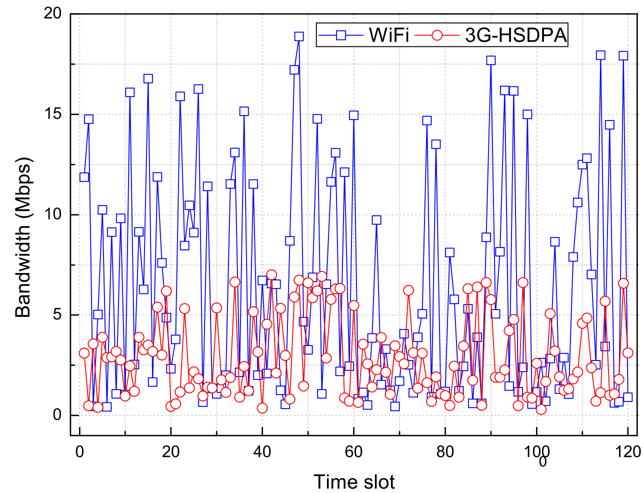
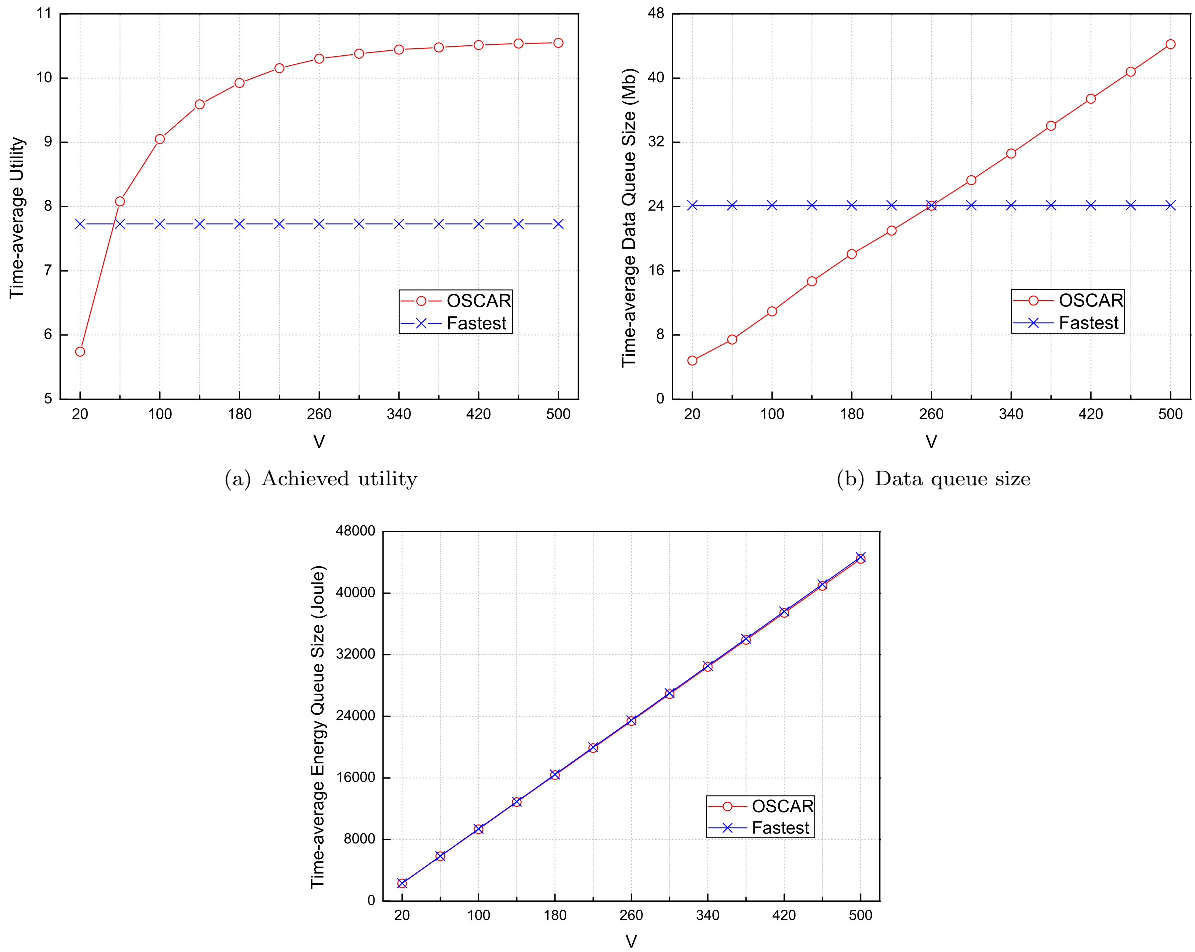


Fig. 1. Twenty-hours trace of uplink throughput for different wireless interfaces.

Moreover, we compare the theoretical and the experimental upper bound of queue backlogs of Q_1 under this setting. The results are shown in Table 2. In our experiments, the queue backlogs are smaller than the mathematical bounds, especially when V is relatively larger. The results in Table 2 are consistent with (19)–(21) of Theorem 1.

In the second set of experiments, we fix $V = 60, 140, 500$, respectively, and vary T from 1000 time slots to 10000 time slots, which is a sufficient range for exploring the characteristics of different timescales of long-time operation. The results are depicted in Fig. 3. It is obvious to us that changing T has very small impacts on the system stability. For example, as shown in Fig. 3(a), the time-average utility only fluctuates within $[-0.83\%, +0.93\%]$, $[-0.33\%, +0.52\%]$, and $[-0.44\%, +0.28\%]$ for $V = 60, 140, 500$, respectively. This confirms that the OSCAR algorithm can guarantee stable performance over time.

In the third set of experiments, we fix $T = 10000$ time slots, and then run simulation experiments with different h_{max} values. As mentioned in Section 2, h_{max} represents the amount of harvestable energy for the device battery. From Fig. 4, we can see that with the growth of h_{max}, OSCAR is able to achieve relatively higher objective utilities with relatively lower data queue backlogs, as shown in Fig. 4(a) and



(a) Achieved utility (b) Data queue size

(c) Energy queue size

Fig. 2. OSCAR performance under different V value.

Table 2
Comparison on theoretical (TH) and experimental (EX) upper bounds of Q_1 and E under different V value.

V	20	60	100	140	180	220	260	300	340	380	420	460	500
Q_{TH}	120	320	520	720	920	1120	1320	1520	1720	1920	2120	2320	2520
Q_{EX}	20	20.4	23.6	28.7	34.8	41.5	45.9	52.1	58.3	63.4	68.6	73.0	78.9
E_{TH}	2368.1	5899.8	9431.5	12963.2	16494.9	20026.6	23558.3	27090	30621.7	34153.4	37685.1	41216.8	44748.5
E_{EX}	2360.1	5883.4	9412.1	12943.2	16474.9	20006.6	23538.3	27070	30601.7	34133.4	37665.1	41196.8	44728.5

(b). This is because when the device is able to obtain more replenishment for each time of energy harvesting, it will have more opportunities to use the wireless interface currently having a higher bandwidth (according to the rule in (18)). As a result, it is more capable of transmitting admitted data in the data queues and admitting new data into the data queues. However, the total amount of available opportunities is limited when other system conditions being the same. Thus, we can notice from Fig. 4(a) and (b) that the gap between curves becomes much smaller as h_{max} grows from 20 to 1000. As shown in Fig. 4(c), in our experiment the value of ϕ is considerably larger than that of h_{max}, so the increment of h_{max} has little impact on the size of energy queue (according to (20)).

5. Related work

The contribution of this work lies in the intersection of the following two important research topics.

5.1. Energy-harvesting sensing system

The proliferation in Micro-Electro-Mechanical-System (MEMS) has facilitated the development of smart sensors. These small, inexpensive sensors could be equipped on a specialized wireless node [17] or a common mobile device [19] to sense, measure and gather information from the environment. Such embedded sensing systems are commonly powered using finite capacity batteries, and the energy supply has become a severe bottleneck. Various studies have been conducted to increase battery lifetime and improve energy efficiency, including data compression [20], modulation optimization [21] and protocol design (e.g., MAC [22], routing [23]). More recently, another alternative has been explored to address the problem of finite battery lifetime: harvesting energy from the environment. There have been many harvesting aware communication schemes that take into account and exploit the energy harvesting characteristics to optimize wireless sensing systems. [24] develops energy management algorithms for a sensor node to achieve maximum packet capacity

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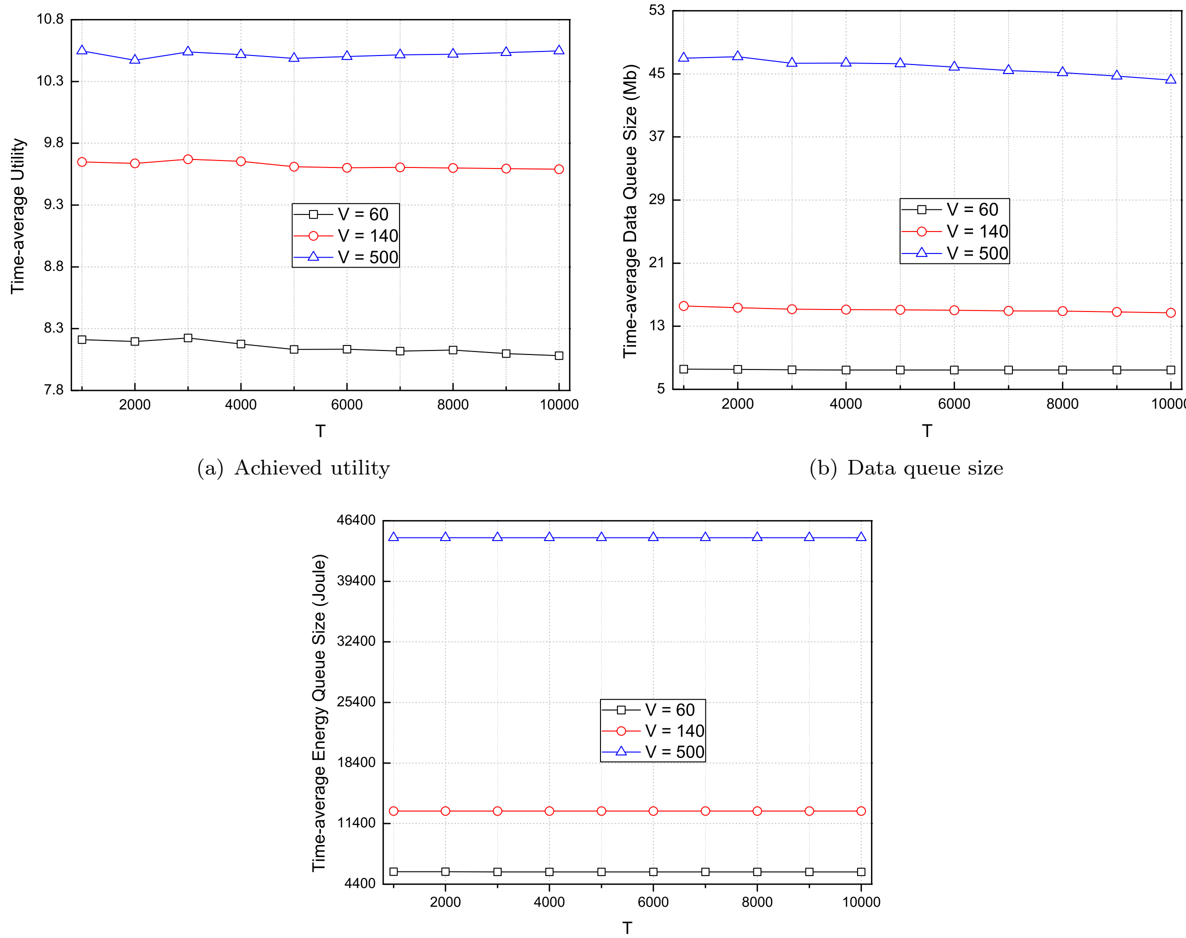


(a) Achieved utility (b) Data queue size

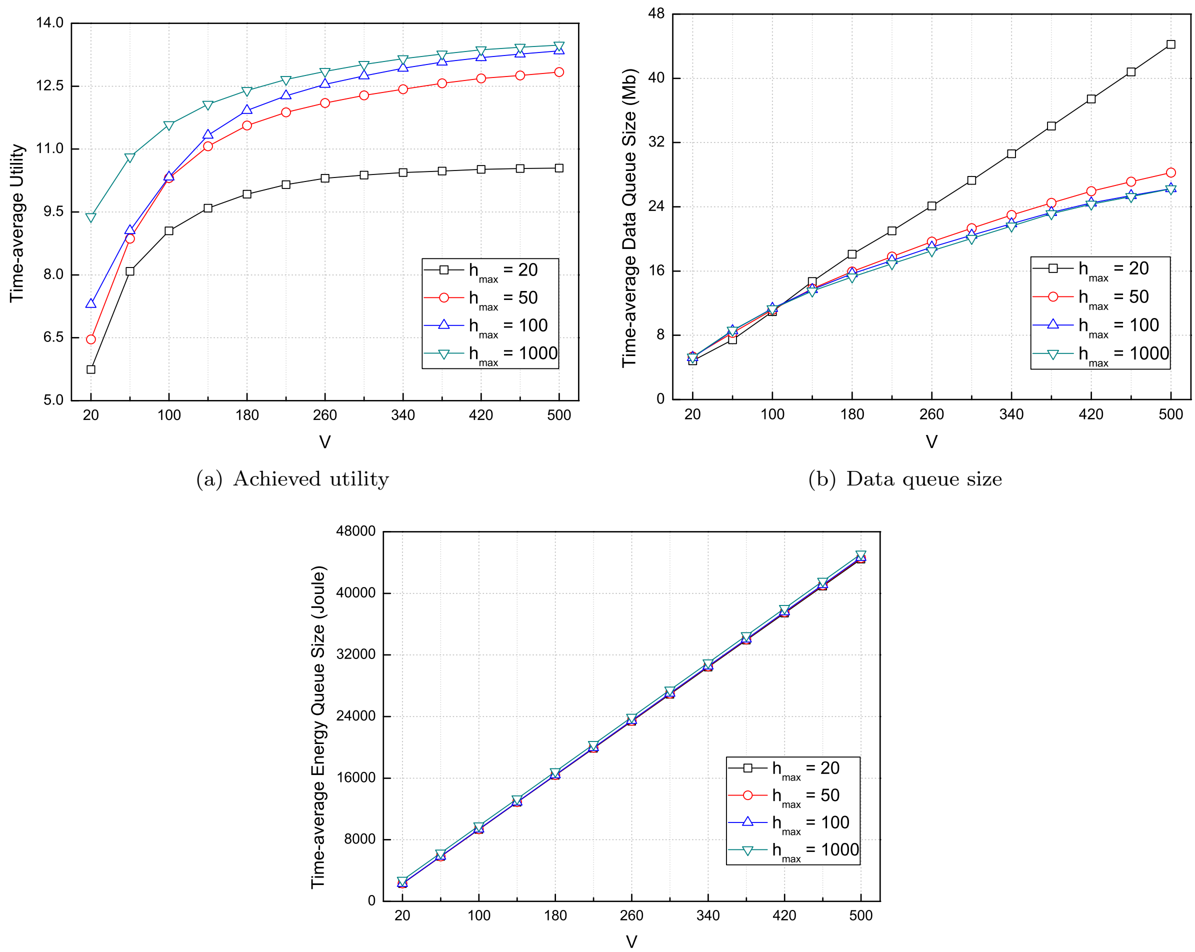
(c) Energy queue size

Fig. 3. OSCAR performance under different *T* value.

and minimum queue delay when the energy-rate function is linear. [25] exploits the node's knowledge of current energy level and the state of the processes of data generation and battery recharge to select the appropriate transmission state for maximize the quality of coverage. [26] presents an optimized wind energy harvesting system that uses a specially designed ultra-low-power-management circuit for sustaining the operation of a wireless sensor node. In [27], the authors propose offline packet scheduling algorithms for a single-user wireless communication system to minimize the transmission completion time by controlling the transmission rate and power. [28] develops a dynamic energy-oriented scheduling scheme to achieve a balance between the system's available energy and the energy consumption of tasks in real time. [29] proposes low-complexity transmission policies for optimizing the data reporting performance of an energy harvesting sensor in the presence of the stochastic ambient energy source. Interested readers can referred to the surveys [5,10] for more progresses in this field of research. Most of the aforementioned work are based on Markov Decision Theory and Dynamic Programming [30]. However, these traditional techniques require more stringent system modelling assumptions and statistical knowledge of system dynamics, and cannot necessarily adapt if these statistics change and/or if there are unmodeled correlations in the actual processes [31]. Moreover, the aforementioned studies assume that the sensor node is always kept in the active state, whereas in practice, the node can periodically cycles between the active state and the sleep state for energy saving [32].

5.2. Lyapunov optimization framework

Lyapunov optimization is a newly proposed technique for solving problems of joint system stability and performance optimization on stochastic networks, especially the communication and queueing systems. The basic idea of this framework is to make control decisions that greedily minimize a bound on the drift-plus-penalty expression over fixed-length time slots , so as to optimize the time averages of certain quantities [8]. Unlike traditional Dynamic Programming and Markov Decision Theory [33], Lyapunov optimization does not require the statistical knowledge of relevant stochastic models, but instead the queue backlog information, to make online control decisions. It has a good computational complexity, and is easy to be implemented in reality. This new theory has been applied in solving many optimization problems on stochastic systems, including power/cost management in smart grid [31,34,35], workload/resource scheduling among data centers [18,30,36], and performance optimization for mobile/wireless systems [7,11,15,37,38]. Among them, our paper is mostly related to the recent work [7,38], both of which use a similar Lyapunov optimization approach for algorithm design. However, the work [7] is designed for more powerful mobile computing devices, and has different system models and optimization objective from ours. Moreover, the algorithm in [7] is constructed based on a two-timescale Lyapunov optimization approach [18], which is unnecessarily complex for resource-constrained sensing devices. The other work [38] is proposed for the utility optimal scheduling



(a) Achieved utility (b) Data queue size

(c) Energy queue size

Fig. 4. OSCAR performance under different h_{max} value.

problem in multi-hop energy-harvesting networks. The model and algorithm in [38] are not suitable for the mobile sensing devices in this paper.

6. Conclusion

This paper addresses transmission utility maximization among sensory data flows for the energy harvesting mobile sensing device powered by a finite battery. A new scheduling algorithm, OSCAR, is proposed that can achieve utility optimality with system stability guarantee using Lyapunov optimization techniques. Different from existing works that heavily relied on prediction-based or statistical offline approaches [5,33], OSCAR is an online algorithm and does not require any statistical knowledge of the harvestable energy processes. Especially, it can approach the optimal utility within a diminishing gap of $\mathcal{O}(1/V)$ with a battery of $\mathcal{O}(V)$ size, while bounding the traffic queue backlog by $\mathcal{O}(V)$, where $V > 0$ is a tunable control parameter. The parameter V empowers system operators to make flexible design choices among various tradeoff points between system stability and utility optimization. Besides, OSCAR can ensure stable performance over time. This algorithm does not require complicated computation, and all the control operations are well supported by common mobile devices nowadays. It will be our future work to evaluate OSCAR using a prototype implement on the modern mobile device platform [4,15,39].

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