Computer Communications 75 (2016) 62–70

Contents lists available at ScienceDirect

Computer Communications

journal homepage: www.elsevier.com/locate/comcom

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

ARTICLE INFO

Article history:
Received 9 February 2015
Revised 4 September 2015
Accepted 7 September 2015
Available online 12 September 2015

Keywords:
Mobile sensor
Energy-harvesting
Lyapunov optimization
Dynamic scheduling
Queueing analysis

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).

http://dx.doi.org/10.1016/j.comcom.2015.09.010
0140-3664/

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