Journal of Network and Computer Applications 44 (2014) 152–160

Contents lists available at ScienceDirect

Journal of Network and Computer Applications

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

Achieving optimal admission control with dynamic scheduling in energy constrained network systems

Weiwei Fang [a,b,*], Zhulin An [c], Lei Shu [d], Qingyu Liu [a], Yongjun Xu [c], Yuan An [b]

[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
[d] Guangdong Provincial Key Lab of Petrochemical Equipment Fault Diagnosis, Guangdong University of Petrochemical Technology, Maoming 525000, China

ARTICLE INFO

Article history:
Received 21 January 2014
Received in revised form
19 April 2014
Accepted 19 May 2014
Available online 9 June 2014

Keywords:
Dynamic scheduling
Optimal control
Admission control
Energy efficiency
Renewal system

ABSTRACT

This paper considers optimization of time average admission rate in an energy-constrained network system with multiple classes of data flows. The system operates regularly over time intervals called frames, while each frame begins with a fixed-length active period and ends with a variable-length idle period. At the beginning of the frame, the system chooses a service mode from a collection of options that affect the class and the amount of data flow served as well as the energy incurred in the active period. After service, the system chooses an amount of time to remain idle. The optimization goal is to make decisions over time that maximizes a weighted sum of admitted data rates subject to constraints on queue stability and energy expenditure. However, conventional solutions suffer from a curse of dimensionality for systems with large state space. Therefore, using a generalized Lyapunov optimization technique, we design a new online control algorithm that solves the problem. The algorithm can push time average admission rate close to optimal, with a corresponding tradeoff in average queue backlog. Remarkably, it does not require any knowledge of the data arrival rates and is provably optimal.

1. Introduction

In this paper, we consider a type of network system that processes and transmits data information with a limited energy supply. There are totally N classes of data flows, while raw data of each class arrive randomly and are stored in separate queues to await service. The system operates over time intervals called frames. Each frame r begins with a fixed-length active period of size D and ends with a variable-length idle period of size $I[r]$. At the beginning of the rth frame, the system chooses a service mode $m[r]$ from a collection of available options. The mode $m[r]$ determines the class of data flow and the amount of raw data that it will serve in the active period of frame r, and the resulting energy expenditure. After data processing and transmission, the system chooses an amount of idle time $I[r]$ to be idle. When the (possibly 0) idle period ends, the system wakes up and a new frame is begun. The goal is to design an algorithm for dynamically making decisions to maximize time average system admission subject to stability requirements and energy constraints. This problem has arisen in many network communication scenarios where the users want to maintain the lifetime of resource-constrained node as long as possible, while processing and transmitting data as much as possible. Typical scenarios include sensor-to-sink data reporting in duty-cycled sensor networks (Keshavarzian et al., 2006; Zhang et al., 2013a), and non-real-time data communication in new-generation mobile networks (Deng and Balakrishnan, 2012; Niu et al., 2014).

The Renewal Theory (Gallager, 1996) is a conventional technique for solving such a problem. It can be shown that, based on the renewal-reward theorem (Gallager, 1996), there exists an optimal control algorithm that makes independent and identically distributed (i.i.d) decisions over frames. However, it is usually difficult to choose such a control policy in an online fashion, since this would require a priori knowledge of system statistics and incur excessive computational complexity for finding the i.i.d. policy (Neely, 2013). Furthermore, these solutions result in hard-to-implement systems, since significant re-computation might be incurred when statistics change.

In this paper, we develop a simple dynamic scheduling algorithm to solve the problem stated above based on the recently developed technique of Lyapunov optimization (Neely, 2013). In every frame, this algorithm observes the current queue status, and minimizes a bound on the drift-plus-penalty ratio by making control decisions on flow control and service scheduling. It can

* Corresponding author at: School of Computer and Information Technology, Beijing Jiaotong University, Beijing 100044, China.
E-mail addresses: wwfang@bjtu.edu.cn (W. Fang), anzhulin@ict.ac.cn (Z. An), lei.shu@lab.gdupt.edu.cn (L. Shu), spencerliuqingyu993@gmail.com (Q. Liu), xyj@ict.ac.cn (Y. Xu), 9112533@qq.com (Y. An).

http://dx.doi.org/10.1016/j.jnca.2014.05.009
1084-8045/

obtain a time average admission rate within a deviation of $\mathcal{O}(1/V)$ from the optimum, with an average queue size tradeoff that is $\mathcal{O}(V)$, where V is a non-negative parameter that weights the extent to which admission maximization is emphasized as compared to system stability. The algorithm does not require knowledge of the traffic arrival rates, and naturally adapts if these rates change. Moreover, it is computationally efficient and easy to implement in the practical systems. We thoroughly analyze the performance of this algorithm with rigorous theoretical analysis. We also carried out extensive simulation experiments to demonstrate its effectiveness and adaptiveness. To our knowledge, prior work has not explored such a problem for network systems with renewal frames, and our use of the Lyapunov framework for solving this issue is also novel.

The rest of this paper is organized as follows: Section 2 formulates the objective problem. Section 3 presents the dynamic scheduling algorithm, and Section 4 provides an analysis on performance bounds of our algorithm. Section 5 shows the performance evaluation results. Section 6 reviews some related work. Finally, Section 7 concludes the paper.

2. System model and problem formulation

2.1. System model

Consider a network system s with N classes of data flows, as shown in Fig. 1. Raw data of each class arrive randomly according to an i.i.d. arrival process with rates $\lambda_1, \ldots, \lambda_N$. We assume that there exists a finite constant λ^{max} such that $\lambda_n \le \lambda^{max}$ for all n. These data are stored in separate queues according to their classes. Let $Q_n(t)$ represents the amount of class n data queued at time t. The system operates in continuous time, so the time index t takes values in the set of non-negative real numbers. The value of $Q_n(t)$ is a non-negative real number for all $n \in \{1, \ldots, N\}$ and for all $t \ge 0$. Assume that the system is initially empty at time $t=0$, therefore $Q_n(0) = 0$ for all $n \in \{1, \ldots, N\}$.

The system s makes decisions over renewal frames, as shown in Fig. 2. The first frame is labelled as frame 0 and starts at time 0. At the beginning of each frame $r \in \{0, 1, 2, \ldots\}$, s chooses a variable $c[r] \in \{0, 1, \ldots, N\}$ that specifies which class of data flow will be served, where $c[r] = 0$ is a null choice that selects no data flow to serve and incurs little energy consumption. s also chooses a service mode $m[r]$ from a finite set $\mathcal{M}$ of mode options. The control decisions $c[r]$ and $m[r]$ determine values $\mu_n[r]$ for each $n \in \{1, \ldots, N\}$, representing the amount of class n data flow that can be served in the active period of frame r. They also determine the system processing energy $e[r]$ that is incurred. At the end of the processing time, s chooses an idle time $I[r]$ within an interval $[0, I_{max}]$ for some given non-negative value I_{max}. The energy expenditure in the idle state is often very low and even neglectable (Neely, 2010). Let $T[r] \in [D, D+I_{max}]$ be the total frame size, then all these above can be given by general functions as follows:

$$\mu_n[r] = \hat{\mu}_n[r] = \hat{\mu}_n(c[r], m[r]) \tag{1}$$

$$e[r] = \hat{e}[r] = \hat{e}(c[r], m[r], I[r]) \tag{2}$$

$$T[r] = \hat{T}[r] = D + I[r] \tag{3}$$

It is assumed that second moments of $\mu_n[r]$ and $e[r]$ are bounded by a finite constant d (Neely, 2012b, 2013), so that

$$\mathbb{E}[\hat{\mu}_n[r]^2] \le d \tag{4}$$

$$\mathbb{E}[\hat{e}[r]^2] \le d \tag{5}$$

where (4) and (5) holds regardless of the policy for any control decision.

Then, for each class of data flow $n \in \{1, \ldots, N\}$, we choose from the interval $[0, 1]$ a flow control variable $\gamma_n[r]$, which represents the probability of admitting new randomly arriving data of class n on frame r. This enables the system to decline new data of class n into the queue when Q_n cannot support to handle data in accordance with the raw arrival rate λ_n. It can easily be generalized to the case where arrivals that are not immediately accepted are stored in a buffer for future admission decision.

Finally, for each class of data flow $n \in \{1, \ldots, N\}$, we define $A_n[r]$ as the random number of new arrivals admitted on frame r, which depends on the total frame size $(D + I[r])$ and the admission probability $\gamma_n[r]$. Assume that the arrival vector $(A_1[r], \ldots, A_N[r])$ is conditionally independent of the past, and with expectations (Neely, 2012b):

$$\mathbb{E}[A_n[r]] = \lambda_n \gamma_n[r] \hat{T}[r] \tag{6}$$

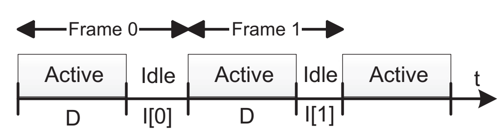

Fig. 2. A timeline illustrating the active and idle periods for each frame.

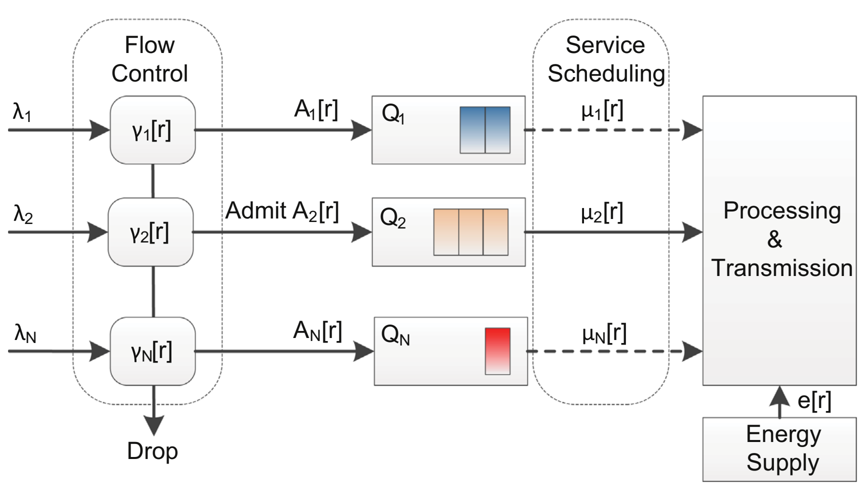

Fig. 1. A network system with random arrivals, flow control and service scheduling.