Switching Constrained Maxweight Scheduling for Wireless Networks

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Motivation



Image credit: Ericsson

Motivation

- Dense deployment of base stations (BS) to support peak data traffic
- **Dynamic** activation and de-activation of BS to **optimize energy** usage
- Fast activation dynamics is used to serve the incoming data rate
- Fast activation dynamics leads to large switching overhead,

e.g. hand-offs, state exchange among BSs, and BS start-up costs

System Model

- Downlink time-slotted system with multiple BSs and Users
- Each BS has a separate queue for each connected user
- Cost of operation + switching: c₁(#Active BS) + c₀(#BS switch)



Example: 2 BS, 1 User

System Model

- 1. I.i.d. Arrival and Channel Realization
- 2. BS Activation (When to switch? What to switch to?)
- 3. Channel Observation from Active BS
- 4. Scheduling and Departure (What to Schedule?)



Problem Definition

• Performance Metrics: 'Asymptotic time average of expected ...'

- 1. Average Cost (Operational + Switching)
- 2. Average Queue Length
- 3. Queue Length Tail

| Minimize | Average Cost |
|------------|---|
| Subject to | Bounded Average Queue Length (Stability) |
| | Exponential decay in Queue Length Tail |
| | Over all Causal policies |
| | (A policy is causal iff it only depends on the history) |

Fixed BS activation

- Capacity region for a fixed BS activation
 Set of arrival rate for which Stability is feasible
- What to schedule using active BSs? [Solved] [L. Tassiulas et al. '92] Static-split among Active BS-User matching Max-weight Active BS-User matching
- We focus on **BS Activation and Switching**



Optimal Activation

• Optimally time share between activations (I.i.d. BS activation)



Scope for Improvement

- Static activation is not adaptive to the queue lengths
 BS1 activated w.p. 0.2, even if Q1 Large and Q2 Small !
- Linear decay in queue length tail under Slow Markov Activation $\mathbb{P}(Sum \ of \ Queue \ lengths \ge x) \le \frac{c}{r}$
- Queue Dependent BS activation with constrained switching
- Prior works without constrained switching A Gopalan et al. '07, MJ Neely et al. '08, MJ Neely et al. '12

Queue Dependent BS Activation



Example: 2 BS 1 User

- Prioritize service for large queues greedily
 Drift(Channel, BS activation) := Sum of (Queue Length × Departure)
- Penalize BS activation for operational cost. **Penalty** := # Active BS
- Constraint Switching between activation
- Algorithm I (LASS-Static):

W.p. ϵ_{sw} Activate

ArgMax Expected (Drift – V × Penalty)

O/w: Stick to Previous BS activation

V: Penalty Scale ϵ_{sw} : Switching Rate



BS Activation Function

Drawback of Static Switching

lacksquare



- We start with BS2 ON
 - In points

 and
 switching of BSs is allowed
 - In Previous BS Subset = Best BS Subset No switching even though it is allowed Switching resource/opportunity is wasted
- In Previous BS Subset ≠ Best BS Subset
 We switch to Both ON from BS2 ON

Dynamic Switching

Algorithm II (LASS-Dynamic): Only differs in 'When to Switch?' Virtual Objects: Switch Queue and Switch Counter

- W.p. *e_{sw}* remove one packet from Switch Queue [Black dots in the plot]
- Current BS activation is not optimal: Increment Switch Counter [2 to 3]



Dynamic Switching

- BS switching when **Switch Counter** ≥ **Switch Queue** [3: Red Dot]
- BS switching: 1) Reset Switch Counter

2) Add packet to Switch Queue



Main Results

Parameters

- #BS: N # Users: M Capacity gap: $\epsilon_g > 0$
- Queue Length at time t: Q(t)
- Optimal cost without switching cost: C^*_{avg}
- Switching rate: ϵ_{sw} , Penalty scale: V (Tuning Knobs)

Time Average bounds

Both LASS-Static and LASS-Dynamic

$$Q_{avg} \leq O\left(\frac{C_{avg}^{*}}{\epsilon_{g}} + V + \frac{NM}{\epsilon_{g}\epsilon_{sw}}\right) \qquad C_{avg} \leq C_{avg}^{*} + O\left(\epsilon_{sw} + \frac{NM}{V\epsilon_{sw}}\right)$$
$$V \uparrow, \epsilon_{sw} \downarrow \Rightarrow Q_{avg} \uparrow, (C_{avg} - C_{avg}^{*}) \downarrow$$

Main Results

Tails Bounds

For large enough x and all time t

- For LASS Static: $\mathbb{P}(|Q(t)| \ge x) \le \exp(-\Theta(\epsilon_{sw}\epsilon_g)x) + O(\frac{\log(t)}{t})$
- For LASS Dynamic: $\mathbb{P}(|Q(t)| \ge x) \le \exp(-\Theta(\epsilon_g)x) + O(\frac{\log(t)}{t})$

Decay rate of LASS Static Depends on ϵ_{sw}

Simulation Results

- Three algorithms for 8 Users and 3 BSs simulated until convergence
- **DP**: **Drift + Penalty (Baseline** with NO Switching Cost)
- LSG: LASS Static
- LD: LASS Dynamic

Simulation Results

- First Plot: Q_{avg} of DP < LD < LSG (V = 100, load = 0.9)
- Second plot: C_{avg} of DP > LD \approx LSG (V = 100, ϵ_{SW} = 0.1)



Simulation Results

- Separation of queue length tail distribution
 - **DP < LD << LSG** (V = 100, load = 0.9)
 - Differences are more pronounced for smaller ϵ_{sw}



Thanks!

Step I: Arrival and Channel Realization

- Arrival and Channel process
 - $\circ~$ I.i.d. across time slots and possibly correlated in a time slot





Example: 2 BS 1 User

Step II: Base Station Activation

- Activate a subset of BSs
- Cost of operation + switching at time t

 $C(t) = c_1(\#Active BS) + c_0(\#BS \, switch)$



Green: Active Blue: Inactive $C(t) = c_1 + 2c_0$

Step III: Channel Observation



- Observe channel after activation
- Why? Probing channel requires energy

Step IV: Scheduling

'Active BS'- User matching

- Each user can connect to at most one BS
- Each BS can connect to at most one user



Switching Constrained Max-weight Scheduling Objective

Minimize cost subject to exponential decay

Minimize C_{avg}^{ϕ} Subject to: ϕ is a causal policy Exponential Decay: $\exists c > 0, \forall t$, large x $\mathbb{P}^{\phi}(|Q(t)|_1 \ge x) \le exp(-cx)$

System is stable :
$$Q_{avg}^{\phi} < \infty$$

Exponential Decay implies Stability

Switching Constrained Max-weight Scheduling How to Schedule?

Edge Weight (BS n, User m): If BS n is active: $Q_{nm}(t)H_{nm}(t)$ Otherwise: 0

Schedule the Max Weight Matching



Switching Constrained Max-weight Scheduling What to Switch to?

Drift+Penalty Method

Best BS Subset maximizes (Expected Weight(J) – V|J|)

Expected Weight(J) = $\sum_{h} \hat{\mu}_{h} M W_{h}(J)$

J : A BS subset $\hat{\mu}_h$: Channel Probability Estimates

 $MW_h(J)$: Value of Max-weight matching

- 1) BS Subset **J** is active
- 2) Channel state h occurs

Switching Constrained Max-weight Scheduling What to Switch to?



Best BS Subset Vs Queue Lengths

Switching Constrained Max-weight Scheduling What to Switch to?



 $J^*(t)$: Best BS Subset. The one to switch to.

Switching Constrained Max-weight Scheduling Drift Equation



Use Lyapunov Function: $|Q(t)|_1^2 + T(t)$