Announcements

- HW 5 due this week
- Final – Friday Dec. 18, 8-10, this room
  - one out of class question

Last 2 classes
- opportunistic scheduling
- opportunistic routing
Wireless effects

- Data carried by electromagnetic waves broadcast from antenna
- Waves oscillate around certain carrier frequency
- Signal arrives weakened at receiver due to distance (path loss), and blocking obstacles (shadowing)

Large scale effects

- Many reflections of same signal arrive at receive antenna causing multi-path fading

Small scale effects

- Wireless channels vary with time, space, frequency. Wireless signals modeled as random signals

Wireless = Randomness
Diversity helps against randomness
Opportunistic Scheduling

Liu, Chong, Shroff paper
slides adapted from Chong
Wireless networking challenges

- low bandwidth, error-prone channels, time-varying characteristics
- limited resource - radio frequency
- demand for wireless rapidly increasing

⇒ techniques needed to improve use of wireless spectrum
Cellular wireless

- each cell contains base station that communicates with mobile users in cell
- wireless capacity can be increased by decreasing cell size
Problems with small cell sizes

- cost of base stations and connection to wired backbone
- increased number, rate of inter-cell handoffs
- other engineering factors, such as mobility management, interference control, etc
Networking: power control

- power - precious resource for mobile users
- just enough transmission power should be used to achieve target QoS (such as SINR)
- unnecessarily high transmission power causes higher interference, leading other users to increase their power as well
- issues of stability, convergence, feasibility, and optimality
Time-varying channel conditions

- propagation path loss
  - distance decay factor $D^{-\alpha}$
  - log-normal shadowing with spatial correlation
  - fast-fading component with Rayleigh or Rician distribution
- both received signal, interference time varying
- SINR (Signal to Interference plus Noise Ratio)

$$\text{SINR} = \frac{\text{signal power}}{\text{interference power} + \text{background noise}}$$
Time-varying channel conditions
Variable network performance

- Network performance depends on channel conditions (SINR), signal processing techniques:
  - Voice users get better quality when SINR high
  - Data traffic, higher SINR $\Rightarrow$ higher data rates
  - Adaptation techniques specified in 3G/4G standards

- Even if same "resource" (RF bandwidth) given to different users, resulting performance (e.g., throughput) can differ
Scheduling

Under time-varying channel conditions, which user should be chosen to transmit at each time?
Scheduling

- Goal: scheme to “schedule” users in opportunistic way to exploit channel fluctuations
- scheduling decision depends on
  - channel conditions
  - fairness or QoS requirements
Naïve scheduling

Cell with two users:
- user 1: close to base station with clear channel, high transmit power
- user 2: at edge of cell with very noisy channel, low transmit power

naïve scheme: always let user 1 transmit
- scheme produces good overall throughput; unfair to user 2
System model

- time divided into slots, shared by all users
- slot exclusively used by one user
- user $i$ assigned fraction $r_i$ of slots
- scheduler decides which user to assign at each slot

applicable to
  - time-slotted systems
  - both uplink, downlink
Utility functions

- $U^k_i$ - utility of user $i$ at time $k$ if time slot $k$ is assigned to $i$

- examples
  - throughput
  - throughput - power cost

- different users can have different utilities, even under same channel conditions

- assume utilities for different users are comparable
Scheduling problem formulation

- $r_i$ - long-term fraction of time assigned to user $i$, $\sum r_i = 1$
- given $\vec{U}^k = (U_1^k, \ldots, U_N^k)$, select user for slot $k$
- policy $Q$ - mapping from utility vector space to index set $\{1, \ldots, N\}$
- given $\vec{U}^k$, if $Q(\vec{U}^k) = i$, then user $i$ is assigned to slot $k$

**Objective:** maximize average utility subject to fairness constraints $r_i$
Scheduling problem

- Suppose $\tilde{U}^k$ stationary, $\tilde{U}^k = \tilde{U}$
- Problem is
  \[
  \max_{Q \in \Theta} E \left( U_{Q(\tilde{U})} \right)
  \]
  \[
  \text{s.t.} \quad P(Q(\tilde{U}) = i) = r_i
  \]
  where $\Theta$ is set of all policies
- Note
  \[
  E \left( U_{Q(\tilde{U})} \right) = \sum_{i=1}^{N} E(U_i | Q(\tilde{U}) = i) r_i
  \]
Optimal policy: two users

Two users, $U_1$ and $U_2$ have continuous distribution functions. There exists $v^*$ s.t.

$$P\{U_1 + v^* \geq U_2\} = r_1$$

Optimal scheme:

$$Q(U_1, U_2) = \begin{cases} 1, & \text{if } U_1 + v^* \geq U_2 \\ 2, & \text{otherwise} \end{cases}$$
Optimal policy: general case

General case: multiple users and discontinuities

Policy: \[ Q(\vec{U}) = \arg\max_{i} (U_i + v_i^*) \]

where \( v^* \) satisfies \( P\{Q(\vec{U}) = i\} = r_i \)

Ties broken randomly with appropriately chosen probabilities (see paper)
Properties

Theorem

- policy $Q$ is optimal
- if utilities of different users independent, then

$$E(U_i | Q(\vec{U}) = i) \geq E(U_i)$$

$\Rightarrow$ opportunistic scheduling scheme does not sacrifice any user for overall system optimality
Parameter estimation

- estimate $v_i^*$ based on measurements of channel using stochastic approximation
- consider root finding algorithm for each threshold
  \[ v_i^{k+1} = v_i^k - \alpha^k (P\{Q(\vec{U}, v_i^k) = i\} - r_i) \]
- can show $v_i^k \to v_i^*$ provided $\alpha^k \to 0$
- $P\{Q(\vec{U}, v_i^k) = i\}$?
- $1_{\{Q(\vec{U}, v_i^k) = i\}}$ - unbiased estimate based on measurements of $U_i^k, i = 1, \ldots, N$
Parameter estimation

- update algorithm
  \[ v_{i}^{k+1} = v_{i}^{k} - \alpha^{k} \left( 1_{\{Q(U^{k}, \tilde{v}^{k}) = i\}} - r_{i} \right) \]

- can show that \( v_{i}^{k} \rightarrow v_{i}^{*} \) with high probability under appropriate conditions on \( \alpha^{k} \), e.g., \( \alpha^{k} = 1/k \)

- simulation results show algorithm works well in system
Scheduling procedure

- set initial value of $\mathbf{v}^1$, say $\mathbf{0}$ or estimate based on history
- at each time slot, system performs the following
  
  Estimate $U_i^k$
  - uplink: base station estimates each user’s channel condition, calculates values of $U_i^k$
  - downlink: user $i$ measures its channel condition, calculates $U_i^k$, informs base station
**Scheduling procedure**

- base station decides which user should take the time slot based on the scheduling policy:
  \[ Q(\vec{U}^k) = \arg\max_{i=1,\ldots,N}(U_i^k + v_i^k) \]

- base station updates parameter vector \( \vec{v}^{k+1} \)
  \[ v_i^{k+1} = v_i^k - \alpha^k \left( 1_{\{Q(\vec{U}^k)=i\}} - r_i \right) \]

- downlink, base station transmits to chosen user
- uplink, base station broadcasts ID of selected user, this user transmits in time slot
Time fraction assignment

- In scheduling policy, \( r_i \) fixed; can be used to give different resources to different classes of applications.

- Approaches to choosing \( r_i's \):
  - User bidding
  - Fair sharing
  - Biased sharing
  - Combination of the above
User bidding

- $m_i$ - amount of money user $i$ willing to pay per unit time

- user $i$ gets

$$r_i = \frac{m_i}{\sum_{j=1}^{N} m_j}$$
Fair sharing

- each user gets equal share
  \[ r_i = \frac{1}{N} \]

multiple classes

\[ r_i = \frac{w_i}{\sum_{j=1}^{L} w_j l_j} \]

- \( L \) - number of classes
- \( l_i \) - number users in class \( i \)
- \( w_i \) - class weight for class \( i \)
Biased sharing

- user $i$ gets share
  $$ r_i = \frac{E[U_i]}{\sum_{j=1}^{N} E[U_j]} $$

- scheme favors good users

- weighted biased sharing
  $$ r_i = \frac{w_i E[U_i]}{\sum_{j=1}^{N} w_j E[U_j]} $$

- $w_i$ - weight of user $i$
Case 1: simulation of a cell

- fair sharing to calculate $r_i, r_i = 1/N$
- non-opportunistic fair sharing scheme: round robin
- downlink, co-channel interference from neighboring cells
- path loss, log-normal shadowing
- users move with speeds and directions that change periodically
- 25 users/cell, exponentially distributed on-off periods
Utility values

- users 1, 2: step
- users 3, 4: linear
- users 5-8: S-shape
Case 1

- $S_n/S_r = [0.99, 0.99, 1.00, 1.00, 0.99, 1.01, 1.01, 1.01]$  
- $S_n = \# \text{time slots assigned to user in optimal scheme}$  
- $S_r = \# \text{time slots assigned to user in non-opportunistic (RR) scheme}$
Case 2: impact of estimation errors

- four time-correlated Gaussian processes representing utility sequences for four users
- on-off sojourn time of user exponentially distributed
- parameters

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Simulation: case 2

Compare

- ideal condition; i.e., known thresholds
- estimated thresholds assuming exact values of $U_i$
- estimated thresholds with estimated values of $U_i$
  \[ \hat{U}_i = U_i + e_i, \quad e_i \sim N(0,4) \]
- estimated thresholds with estimated values of $U_i$
  \[ \hat{U}_i = U_i + e_i, \quad e_i \sim N(0,8) \]
Simulation: case 2

Utility improvement, normalized over RoundRobin
Summary

- developed an optimal opportunistic scheduling scheme with explicit fairness constraints
- simulation results indicate that opportunistic policies enjoy substantial gains over non-opportunistic policies (in terms of overall utility)
- preliminary results indicate robustness to estimation errors
- advantages: simple/implementable policy, nonrestrictive model assumptions

Similar opportunistic scheduling policies used in cellular systems
Other topics

- incorporate practical estimation of channel conditions, errors
- short term fairness
- explicit delay constraints
- maximize system performance under minimum utility guarantees