Resource Management in QoS-Aware Wireless Cellular Networks

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Thesis Work

A framework for opportunistic scheduling in multiuser OFDM systems

Tradeoff between system performance and QoS/fairness for individual users in multiple-channel systems.

A generalized framework for opportunistic scheduling

Incorporate heterogeneous QoS support into opportunistic scheduling, provide an efficient tool (problem formulation and solution) to design and analyze this category of fair scheduling.

Stochastic dynamic programming for opportunistic scheduling

An approximate dynamic programming approach for opportunistic scheduling in a more generalized network model (finite queue backlogs and channel memory).

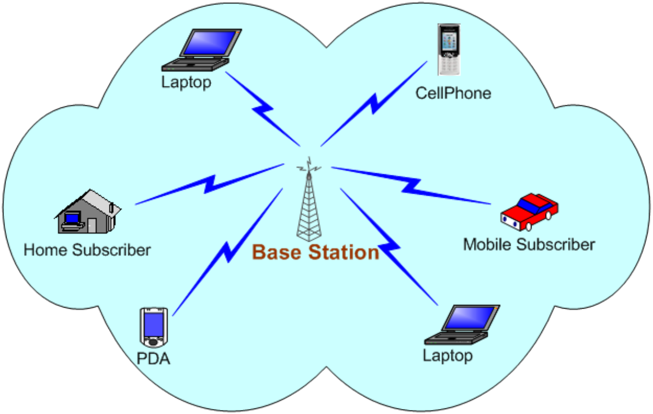
Publications

- Journal
  - Z. Zhang, Y. He, and E. K. P. Chong, "Opportunistic scheduling for OFDM systems with fairness constraints," *EURASIP Journal on Wireless Communications and Networking*, vol. 2008, Article ID 215939, 12 pages, 2008.
  - Z. Zhang, S. Moola, and E. K. P. Chong, "Opportunistic fair sheduling in wireless networks: an approximate dynamic programming approach," *ACM Mobile Networks and Applications (MONET)*, in revision, 2008.
  - Z. Zhang and E. K. P. Chong, "Opportunistic scheduling with heterogeneous QoS support," in preparation.
  - Z. Zhang, L. L. Scharf, and E. K. P. Chong, "Algebraic equivalence of matrix conjugate direction and matrix multistage Wiener filters," in preparation.
- Conference
  - Z. Zhang, S. Moola, and E. K. P. Chong, "Approximate stochastic dynamic programming for opportunistic fair scheduling in wireless networks," 47th IEEE CDC, Cancun, Mexico, December 9–11, 2008, pp. 1404–1409.
  - Z. Zhang, Y. He, and E. K. P. Chong, "Opportunistic downlink scheduling for Multiuser OFDM systems," IEEE WCNC'05, New Orleans, LA, March 13–17, 2005,pp. 1206–1212 (Invited paper).
  - L. L. Scharf, E. K. P. Chong, and Z. Zhang, "Algebraic equivalence of matrix conjugate direction and matrix multistage filters for estimating random vectors," 43th IEEE CDC, Paradise Island, Bahamas, December 14–17, 2004, pp. 4175–4179.
  - L. L. Scharf, E. K. P. Chong, L. T. McWhorter, and Z. Zhang, "Algebraic equivalence of block conjugate direction and block multistage Wiener filters for estimating random vectors," Lake Louise Workshop on The Future of Signal Processing in the 21st Century, Lake Louise, Canada, October 5–10, 2003.

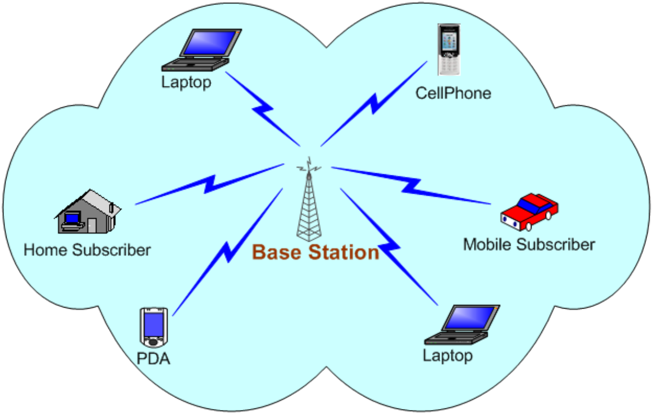
Outline

Outline

Challenges for Future Broadband Wireless Networks



Challenges for Future Broadband Wireless Networks



- High-speed data rate: ~100Mbps to 1Gbps
- Heterogeneous Quality of Service (QoS) provisioning

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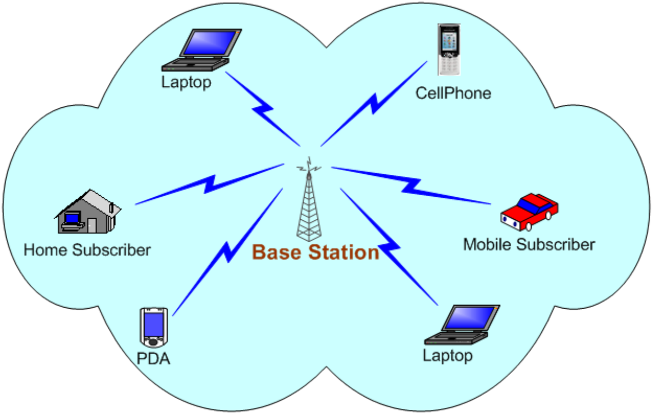


- High-speed data rate: ∼100Mbps to 1Gbps
- Heterogeneous Quality of Service (QoS) provisioning

⇒ Flexible and efficient radio resource management:
Scheduling, admission control, power control, etc.

Characteristics of Wireless Channels

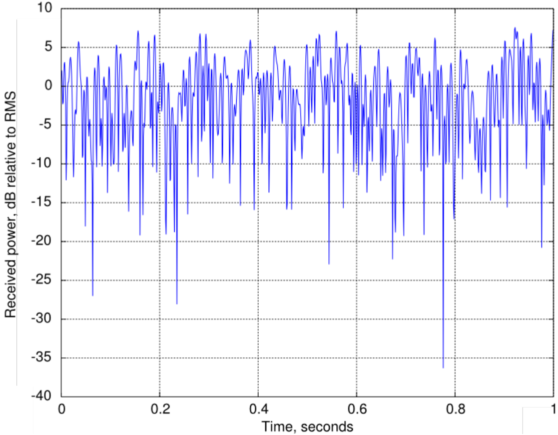


Figure: Rayleigh fading with maximum 100Hz Doppler shift

Characteristics of Wireless Channels

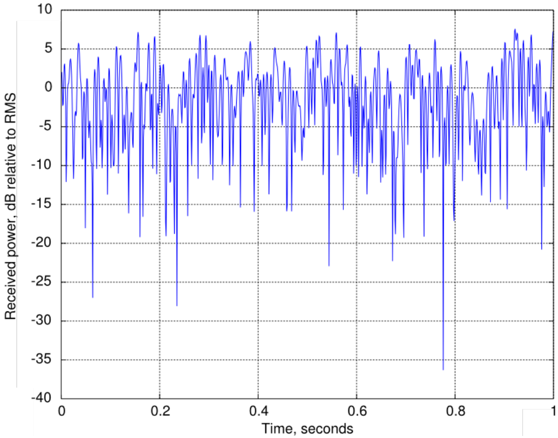
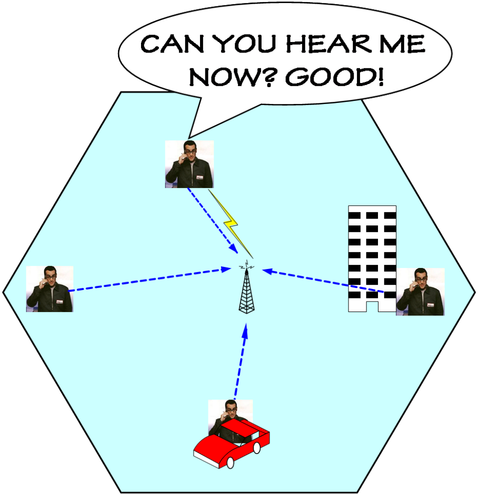


Figure: Rayleigh fading with maximum 100Hz Doppler shift

- Radio propagation: Path loss, shadowing, and multipath fading
- *Time-varying* and *location-dependent* channel conditions

Opportunistic Scheduling: An Illustration



- One base station and several active users in a cell.

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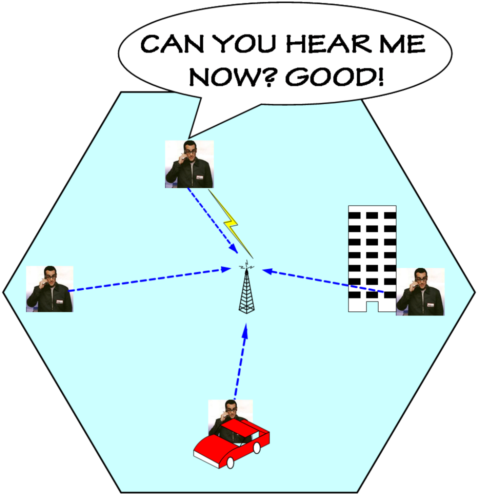

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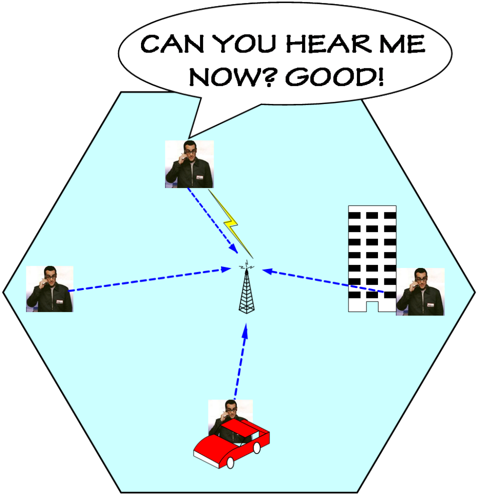

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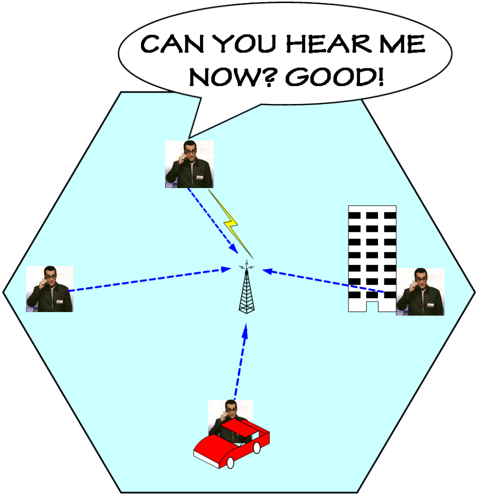


- One base station and several active users in a cell.
- At each time, scheduler picks one user to transmit.
- Channel conditions are time varying and location dependent.
- Scheduling decision is based on channel condition, input queues, QoS constraints, etc.

Outline

Motivation

- Opportunistic scheduling exploits time-varying channel conditions to achieve multiuser diversity.
- Scheduler also should maintain specific QoS/fairness constraints for individual users.
- Previous work treats different QoS constraints individually as different problems.
- Future wireless multimedia networks require heterogeneous QoS support for individual users.
- A single user could require multiple different QoS/fairness constraints.

Motivation for Minimal and Maximal Constraints

- Minimal constraints
  - A minimal guarantee is the natural and simplest QoS guarantee.
  - Bandwidth-sensitive applications need a minimal rate: VoIP and streaming video.
  - Ensure premium customers receive better service than regular customers.
- Maximal constraints
  - Give users an incentive to upgrade to expensive premium services.
  - Decrease the subscribers' QoS sensitivity to the number of subscribers in the network.

Fairness and QoS Requirements

- Scheduler must allocate resources fairly among users under specific QoS/fairness constraints.
- Examples of (long-term) minimal constraints:
  - Temporal fairness: User i is scheduled at least r_i of the time.
  - Utilitarian fairness: User i receives at least a_i of the overall system utility.
  - Minimum-performance guarantee: User i receives at least a utility of C_i.
  - Proportional fairness: Aggregate of proportional change in utility is non-positive.

Scheduling with Generalized QoS constraints

- U_i^t: channel utility for user i at time t. Example: instantaneous throughput.
- The better the channel condition, the larger the value of U_i^t.
- For simplicity, assume that channels are *stationary* and *ergodic*.
- Utility vector: $\vec{U} = (U_1, \cdots, U_N)$, N: number of users, U_i: utility of user i at a generic time-slot.
- Scheduling policy π: a rule that specifies the action at each time.
- Policy π schedules user $\pi(\vec{U}) = i$ to transmit, receives "reward" U_i.
- A *feasible* policy satisfies specific fairness/QoS constraints.

Problem Formulation

$$\max_{\pi} E \sum_{i=1}^{N} f_i(U_i)\mathbf{1}_{\{\pi(\vec{U})=i\}} \tag{1}$$

$$\text{subject to } E\left(h_i^j(U_i)\mathbf{1}_{\{\pi(\vec{U})=i\}}\right) - H_i^j \geq 0, \qquad i = 1, 2, \ldots, N,\ j = 1, 2, \ldots, J,$$

$$E\left(g_i^k(U_i)\mathbf{1}_{\{\pi(\vec{U})=i\}}\right) - G_i^k \leq 0, \qquad i = 1, 2, \ldots, N,\ k = 1, 2, \ldots, K.$$

- f_i: Functions of utility associated with user i.
- h_i^j, g_i^k: Constraint functions associated with user i. We assume that h_i^j and g_i^k are convex.
- H_i^j, G_i^k: Minimum and maximum predetermined constraint requirements associated with user i respectively.

Optimal Scheduling Policy

Define the policy π^* as follows:

$$\pi^*(\vec{U}) = \underset{i}{\operatorname{argmax}} \left\{ f_i(U_i) + \sum_{j=1}^{J} \lambda_i^j h_i^j(U_i) - \sum_{k=1}^{K} \rho_i^k g_i^k(U_i) \right\}, \quad (2)$$

where the control parameters λ_i^j and ρ_i^k are chosen such that:

1. $\lambda_i^j \geq 0$, $\rho_i^k \geq 0$, $\forall i$, $\forall j$, $\forall k$;
2. $E\left(h_i^j(U_i)\mathbf{1}_{\{\pi^*(\vec{U})=i\}}\right) - H_i^j \geq 0$, $\forall i$, $\forall j$;
3. If $E\left(h_i^j(U_i)\mathbf{1}_{\{\pi^*(\vec{U})=i\}}\right) - H_i^j > 0$, then $\lambda_i^j = 0$, $\forall i$, $\forall j$;
4. $E\left(g_i^k(U_i)\mathbf{1}_{\{\pi^*(\vec{U})=i\}}\right) - G_i^k \leq 0$, $\forall i$, $\forall k$;
5. If $E\left(g_i^k(U_i)\mathbf{1}_{\{\pi^*(\vec{U})=i\}}\right) - G_i^k < 0$, then $\rho_i^k = 0$, $\forall i$, $\forall k$.

Theorem

The policy π^* defined in (2), if it exists, is an optimal solution to the problem defined in (1), i.e., it maximizes the system performance while satisfying the general fairness constraints for individual users.

An Example

Scheduling with Minimal and Maximal Data Rates

$$\max_{\pi} \sum_{i=1}^{N} E\left(U_i \mathbf{1}_{\{\pi(\vec{U})=i\}}\right)$$

$$\text{subject to } E\left(U_i \mathbf{1}_{\{\pi(\vec{U})=i\}}\right) \geq C_i, \qquad i = 1, 2, \ldots, N,$$

$$E\left(U_i \mathbf{1}_{\{\pi(\vec{U})=i\}}\right) \leq D_i, \qquad i = 1, 2, \ldots, N.$$

- $\vec{C} = (C_1, C_2, \ldots, C_N)$: a feasible predetermined *minimal data rate requirement vector*.
- $\vec{D} = (D_1, D_2, \ldots, D_N)$: a feasible predetermined *maximal data rate requirement vector*.
- $D_i \geq C_i \geq 0, \ \forall i$.

Optimal Scheduling Policy

The following policy π^* is optimal:

$$\pi^*(\vec{U}) = \operatorname*{argmax}_i \{(\theta_i - \mu_i)U_i\},$$

where the control parameters θ_i and μ_i are chosen such that:

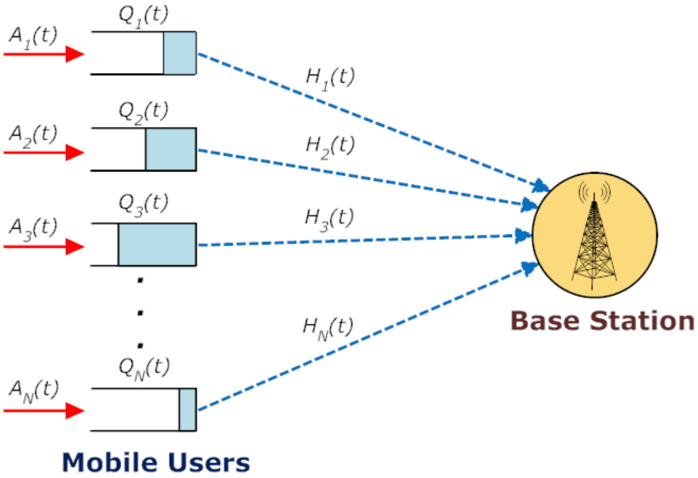
1. $\theta_i \geq 1$, $\mu_i \geq 0$, $\forall i$;
2. $E\left(U_i \mathbf{1}_{\{\pi^*(\vec{U})=i\}}\right) \geq C_i$, $\forall i$;
3. If $E\left(U_i \mathbf{1}_{\{\pi^*(\vec{U})=i\}}\right) > C_i$, then $\theta_i = 1$, $\forall i$;
4. $E\left(U_i \mathbf{1}_{\{\pi^*(\vec{U})=i\}}\right) \leq D_i$, $\forall i$;
5. If $E\left(U_i \mathbf{1}_{\{\pi^*(\vec{U})=i\}}\right) < D_i$, then $\mu_i = 0$, $\forall i$.

Outline

Overview

- Opportunistic scheduling: Multiuser diversity vs. QoS/fairness.
- Memoryless channels vs. channels with memory.
- Delay insensitive traffic vs. delay sensitive traffic.
- Markov decision processes (MDPs) and dynamic programming: Sequential decision making under uncertainty.

A TDM Uplink Queueing Model



Opportunistic Fair Scheduling

- Goal: Maximize system performance under certain QoS requirements of users.
  - Throughput maximization.
  - Delay minimization: Average system queue length.
- Want to determine optimal *scheduler*.
- Scheduling decision at time t depends on
  - Instantaneous channel conditions $H_i(t)$.
  - Packet queue lengths $Q_i(t)$.
  - Exogenous packet arrivals $A_i(t)$.
  - Specific fairness/QoS requirements.
- Fairness constraint considered here: Temporal fairness (long-term).

Problem Formulation as MDP

- Opportunistic scheduling problem formulated as an MDP.
- Consider two creteria: Infinite horizon expected discounted reward and expected average reward.
- MDP is specified by
  - State space
  - Action space
  - Transition function
  - Reward function

Problem Formulation as MDP (Cont'd)

- State space: $\mathcal{S} \subset \mathbb{R}^{2K}$.
  State of system at time t is

  $$X_t = (Q_1(t), Q_2(t), \ldots, Q_N(t), H_1(t), H_2(t), \ldots, H_N(t)),$$

  $Q_i(t)$ and $H_i(t)$ are queue length and channel state of user i at time t. Generic notation of state: $s, s' \in \mathcal{S}$.

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- Action space: $\mathcal{A} = \{1, 2, \dots, N\}$.
  Action at time t is the selected user $i = \pi_t$.
  Generic notation of action: $a \in \mathcal{A}$.

Problem Formulation as MDP (Cont'd)

- Transition function: Determined by
  - Queue-length evolution:

$$Q_i(t+1) = Q_i(t) + A_i(t) - \min\left(Q_i(t), H_i(t)\right)\mathbf{1}_{\{\pi_t = i\}}.$$

  - Dynamics of the channels (Markov chain).

Problem Formulation as MDP (Cont'd)

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  - Dynamics of the channels (Markov chain).
- Reward functions:
  - Throughput maximization:

$$r(X_t, \pi_t) = \sum_{i=1}^{N} \min\left(Q_i(t), H_i(t)\right)\mathbf{1}_{\{\pi_t = i\}}.$$

  - Delay minimization:

$$r(X_t, \pi_t) = -\sum_{i=1}^{N} Q_i(t).$$

Problem Formulation as MDP (Cont'd)

- Given a policy π, the expected average reward is

$$J_\pi(s) = \lim_{T\to\infty} E_\pi \left[\frac{1}{T} \sum_{t=0}^{T-1} r(X_t, \pi_t) \middle| X_0 = s \right], \quad s \in \mathcal{S}.$$

- Want to maximize $J_\pi(s)$ with respect to π.
- Our MDP is nonstandard because of *constraint* on π corresponding to temporal fairness.

Problem Formulation as MDP (Cont'd)

- Expected average temporal fairness constraint:

$$\lim_{T \to \infty} E_\pi \left[\frac{1}{T} \sum_{t=0}^{T-1} \mathbf{1}_{\{\pi_t = a\}} \middle| X_0 = s \right] \geq C(a), \quad \forall a \in \mathcal{A}, \tag{3}$$

$C(a)$: minimum relative frequency at which action (user) a should be selected, where $C(a) \geq 0$ and $\sum_{a \in \mathcal{A}} C(a) \leq 1$.

- Let Π be set of all policies satisfying expected average temporal fairness constraint.
- A policy π^* is *average-reward-optimal* if

$$J_{\pi^*}(s) = \max_{\pi \in \Pi} J_\pi(s), \quad \forall s \in \mathcal{S}. \tag{4}$$

Temporal Fair Scheduling Problem

Goal

Find an average-reward-optimal policy π^* subject to the expected average temporal fairness constraint.

- Opportunistic scheduling problem posed as an MDP with expected average temporal fairness constraint.
- Scheduler corresponds to optimal policy.
- How to compute scheduler?

Optimal Scheduling Policy

Suppose the system is unichain. Suppose we have a bounded function $h : \mathcal{S} \to \mathbb{R}$, a function $u : \mathcal{A} \to \mathbb{R}$, a constant g, and a stationary policy π^* such that for $s \in \mathcal{S}$,

1. $\forall a \in \mathcal{A}$, $u(a) \geq 0$;
2. $\forall a \in \mathcal{A}$, $\lim_{T\to\infty} E_{\pi^*}\left[\frac{1}{T}\sum_{t=0}^{T-1}\mathbf{1}_{\{\pi_t^*=a\}}\middle|X_0 = s\right] \geq C(a)$;
3. $\forall a \in \mathcal{A}$, if $\lim_{T\to\infty} E_{\pi^*}\left[\frac{1}{T}\sum_{t=0}^{T-1}\mathbf{1}_{\{\pi_t^*=a\}}\middle|X_0 = s\right] > C(a)$, then $u(a) = 0$;
4. $$g + h(s) = \max_{a\in\mathcal{A}}\{r(s,a) + u(a) + \sum_{s'\in\mathcal{S}} P(s'|s,a)h(s')\}; \tag{5}$$
5. π^* is a policy which, for each s, prescribes an action which maximizes the right-side of (5):
$$\pi^*(s) = \operatorname*{argmax}_{a\in\mathcal{A}}\{r(s,a) + u(a) + \sum_{s'\in\mathcal{S}} P(s'|s,a)h(s')\}.$$

Then π^* is an average-reward-optimal policy as defined by (4) subject to (3). The corresponding optimal average reward is

$$J_{\pi^*}(s) = g - \sum_{a\in\mathcal{A}} u(a)C(a), \quad \forall s \in \mathcal{S}.$$

Remarks on Optimal Scheduling Policy

1. Main result: An *explicit* Bellman's equation for the general temporal fairness constrained MDP.

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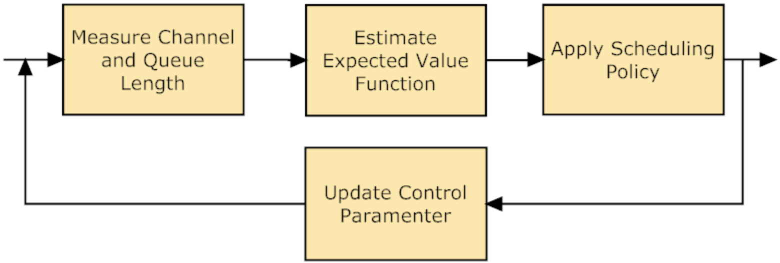
Remarks on Optimal Scheduling Policy

1. Main result: An *explicit* Bellman's equation for the general temporal fairness constrained MDP.
2. Proved sufficiency of Bellman's equation for optimality.
3. Obtained optimal scheduling policy based on Bellman's equation.
4. Developed a novel approximation method: *Temporal fair rollout*.

Temporal Fair Rollout

- An approximation method based on Monte Carlo sampling.
- Builds on [Bertsekas & Castañon 1999] by incorporating temporal fairness constraints.
- Optimal value function is approximated by some base policy: Typically heuristic and suboptimal.
- Rollout achieves better performance than base policy $\Rightarrow$ *reward-improvement property*.

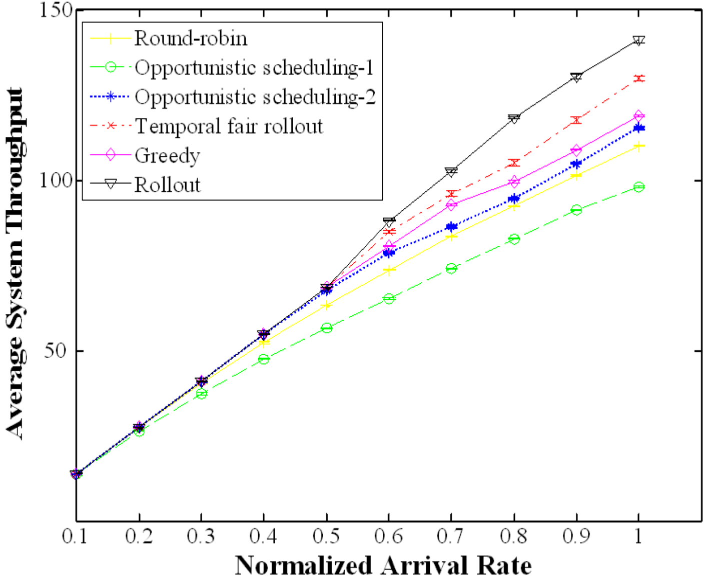
Stochastic Approximation for Parameter Estimation



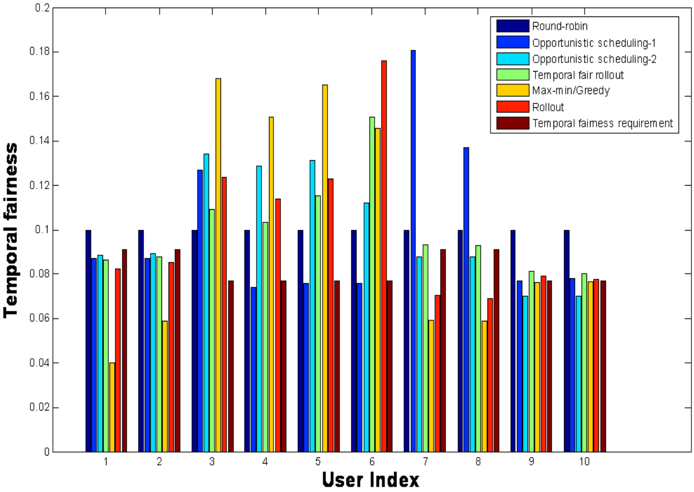
Scheduling Schemes for Evaluation

1. Round-robin: Schedule users in predetermined order.
2. Opportunistic scheduling-1: Infinite-backlog temporal fairness policy [Liu, Chong, Shroff 2003].
3. Opportunistic scheduling-2: Variation of *opportunistic scheduling-1* with consideration of queue lengths.
4. Temporal fair rollout: Base policy is *opportunistic scheduling-2*.
5. Greedy: Schedule user with best channel condition ($\notin \Pi$).
6. Rollout (unconstrained): Base policy is greedy policy ($\notin \Pi$).

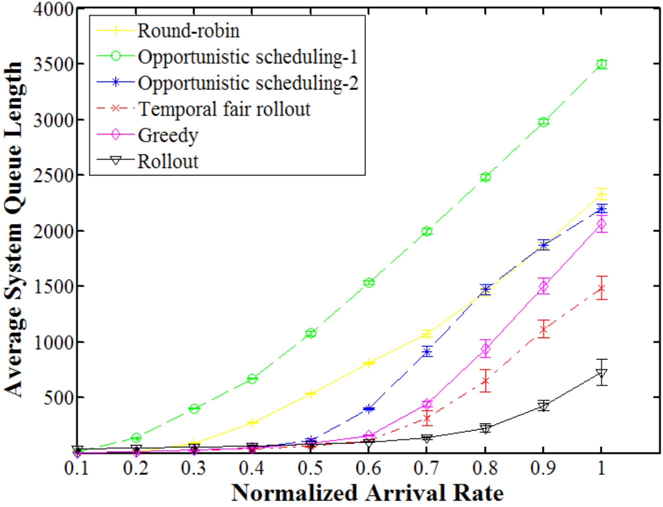
Performance for Throughput Maximization Problem



Fairness in Throughput Maximization Problem



Performance for Delay Minimization Problem



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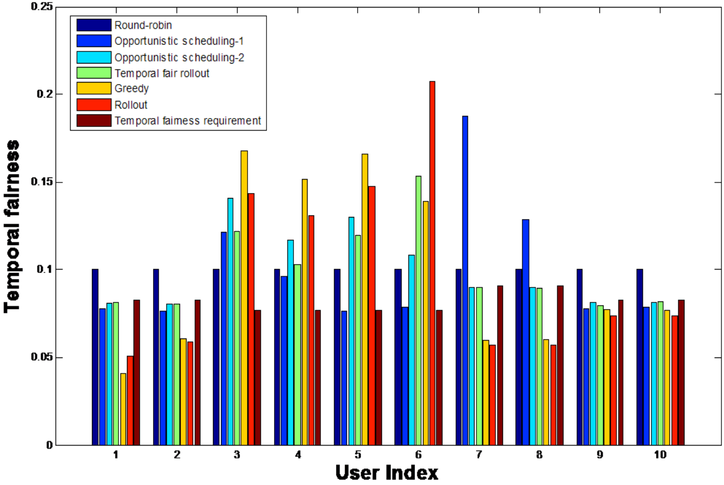

Outline

Summary

- Opportunistic scheduling exploits time-varying, location-dependent channel conditions to achieve mulituser diversity.
- Our framework for opportunistic scheduling in multiuser OFDM systems exploits both multiuser diversity and frequency diversity *opportunisitically* while maintaining certain QoS/fairness constraints for individual users.
- Our generalized framework for opportunistic scheduling encompasses most previous opportunistic fair scheduling formulation and also provide an efficient tool to design and analyze the scheduling problems with general heterogeneous QoS constraints.
- We reformulate the fair scheduling problem as a constrained MDP in a more general setting. The proposed approximate dynamic programming approach can easily be extended to fit different objective functions and other fairness measures.