Optimal Scheduling in High Speed Downlink Packet Access

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Objective and Motivation

Methodology

Problem Definition and Model Description

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- Fair; Divide the resources fairly between all the active users.
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- Provide channel aware (diversity gain) and high speed resource allocation.

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- This resulted in many different scheduling techniques and implementations most of which are proprietary.
- Most of the available work in scheduler design is based on intuition and creativity of the designers. This approach can be described as a *procedural approach* and works as follows:

Motivation cont.

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- Then tries to establish confidence in it using backward analysis or simulation.
- This, will result in a suboptimal algorithm at the best, that performs well in some scenarios and poor in the others.

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  - Must be solvable.

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  - Can easily be extended to larger queue sizes.

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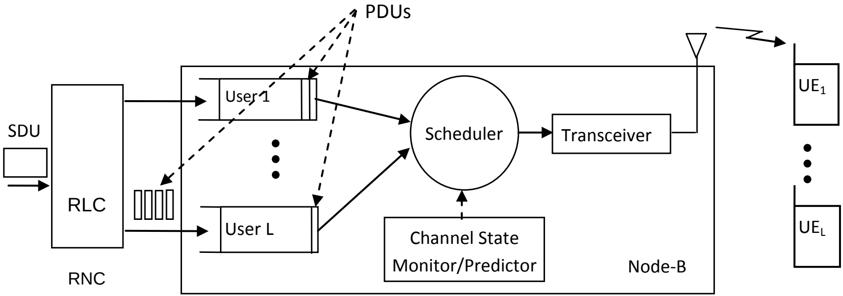
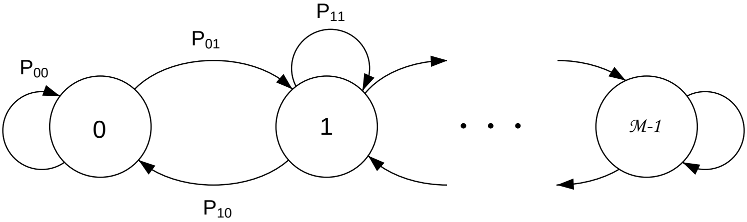
- Time is slotted into fixed length 2 ms TTIs.
- During each TTI, there are 15 available codes that may be allocated to one or more users.

HSDPA Scheduler Model (Downlink)



FSMC Model for HSDPA Downlink Channel



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  - $R(\mathbf{s}, \mathbf{a})$ is the immediate reward when at state **s** and taking action **a**.

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- Independent Bernoulli arrivals with parameter q_i.
- Scheduler can assign c codes chunks at a time, where $c \in \{1, 3, 5, 15\}$.

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- user i channel can handle up to $\gamma_i(t)$ PDUs per code.
- The Markov transition probability $P_{\gamma_i \gamma_i'}$ is known and can be calculated for any mobile environment with Rayleigh fading channel [Wang and Moayeri].

State

- The system state $\mathbf{s}(t) \in S$ is a vector comprised of multiple state variables

$$\mathbf{s}(t) = (x_1(t), x_2(t), \ldots, x_L(t), \gamma_1(t), \gamma_2(t), \ldots, \gamma_L(t)) \quad (1)$$

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- $S = \{\mathcal{X} \times \mathcal{M}\}^L$ is finite, due to the assumption of finite buffers size and channel states.

Action Sets

- The action $\mathbf{a}(\mathbf{s}) \in A$ is taken when in state $\mathbf{s}$

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- The first constraint means that the policy can not allocate more than the available 15 codes at each time slot.
- The second makes the policy conservative by allocating no more codes to user i than that required to empty its buffer.

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- $R(\mathbf{s}, \mathbf{a})$ have two components corresponding to the two objectives

$$R(\mathbf{s}, \mathbf{a}) = \sum_{i=1}^{L} a_i \gamma_i c - \sigma \sum_{i=1}^{L} (B - \bar{x})\, \mathbf{1}_{\{x_i = B\}} \qquad (3)$$

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- The second term guarantees some level of fairness and reduces dropping probability.

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- where $P_{\gamma_i \gamma_i'}$ is the Markov transition probability of the FSMC.

State Transition Probability cont.

We derived $P_{x_i x_i'}(\gamma_i, a_i)$ using (5) and the law of total probability, and arrived at the following expression

State Transition Probability cont.

- $$P_{x_i x_i'}(\gamma_i, a_i) = \begin{cases} 1 & \text{if } x_i' = x_i = B \text{ \& } a_i\gamma_i = 0, \\ q_i & \text{if } x_i' = x_i = B \text{ \& } 0 < a_i\gamma_i c \le u_i, \\ q_i & \text{if } x_i' = B \text{ \& } x_i < B \text{ \& } W1 \ge B, \\ q_i & \text{if } x_i' < B \text{ \& } x_i' = W1, \\ 1 - q_i & \text{if } x_i' < B \text{ \& } x_i' = W2, \\ 0 & \text{otherwise.} \end{cases} \tag{7}$$

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- where, $V^*(\mathbf{s}) = \sup_{\pi} V^{\pi}(\mathbf{s})$, attained when applying the optimal policy π^*.

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- We can generalize for the infinite horizon average reward using results from [puterman] and [ross].

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- User i is said to be **connected** when $\gamma_i=1$ with probability $P(\gamma_i=1)=\alpha_i/(\alpha_i+\beta_i)$.

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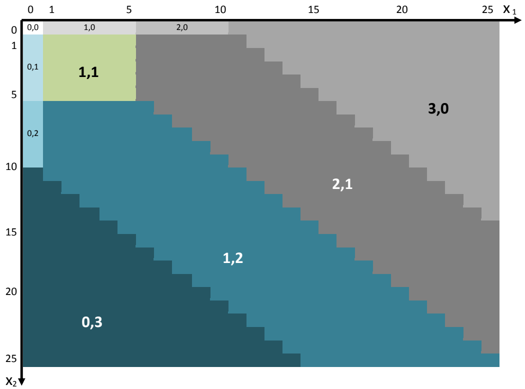
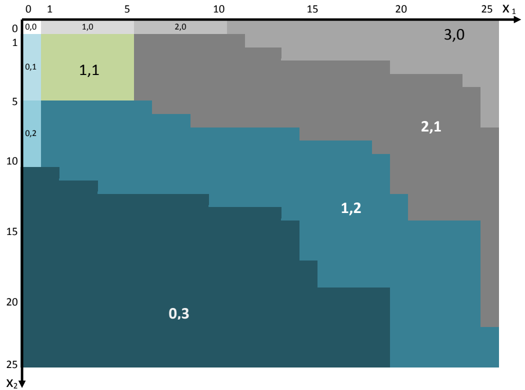
- $B = 25$, $\sigma = 0.5$, $\lambda = 0.95$, $\epsilon = 0.1$, and $c = 3$, 5 or 15.

The Optimal Policy for Two Symmetrical Users



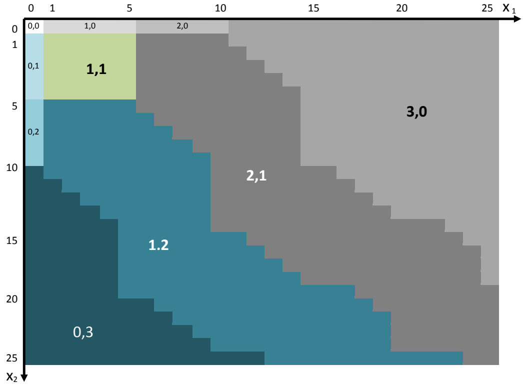
$\alpha_i = \beta_i = p$ for all $0 \leq p \leq 1$ and $P(z_i = 5) = 0.5$ for all $i \in \{1, 2\}$.

The Effect of Channel Quality on Policy Structure



$P(\gamma_1 = 1) = 0.8$ and $P(\gamma_2 = 1) = 0.5$ and $P(z_i = 5) = 0.5$.

The Effect of Arrival Probability on Policy Structure



$$P(\gamma_1 = 1) = P(\gamma_2 = 1) = 0.5 \text{ and } P(z_1 = 5) = 0.8 \; P(z_2 = 5) = 0.5.$$

Heuristic Approach

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- Evaluate the Heuristic policy by comparing the system performance under both policies.

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- The policy is a switch-over and can be described as *share the codes in proportion to the weighted queue length of the connected users*.
- The weight (w_i) is a function of the difference of the two channel qualities and that of the arrival probabilities:

$$w_1 = f([-\Delta P_\gamma]^+, [-\Delta P_z]^+) \quad (11)$$
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Heuristic Policy cont.

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Heuristic Policy for $c = 15$

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- Rule3: when the two users are connected allocate code chunks according to (13) below

$$\mathbf{a}(t) = \begin{cases} (1,0) & \text{if } w_1 x_1 > w_2 x_2, \\ (0,1) & \text{if } w_1 x_1 \leq w_2 x_2 \end{cases} \qquad (13)$$

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$$\mathbf{a}(t) = \begin{cases} (3,0) & \text{if } w_1 x_1 > w_2 x_2 + 10, \\ (2,1) & \text{if } w_2 x_2 < w_1 x_1 \leq w_2 x_2 + 10, \\ (1,2) & \text{if } w_2 x_2 - 10 \leq w_1 x_1 \leq w_2 x_2, \\ (0,3) & \text{if } w_1 x_1 < w_2 x_2 - 10, \end{cases} \tag{14}$$

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$$\mathbf{a}(t) = \begin{cases} (5,0) & \text{if } w_1x_1 > w_2x_2 + 12, \\ (4,1) & \text{if } w_2x_2 + 6 < w_1x_1 \le w_2x_2 + 12, \\ (3,2) & \text{if } w_2x_2 < w_1x_1 \le w_2x_2 + 6, \\ (2,3) & \text{if } w_2x_2 - 6 < w_1x_1 \le w_2x_2, \\ (1,4) & \text{if } w_2x_2 - 12 < w_1x_1 \le w_2x_2 - 6, \\ (0,5) & \text{if } w_1x_1 \le w_2x_2 - 12, \end{cases} \tag{15}$$

Weight Function Approximation

Following these observations, we approximated w_1 and w_2 as follows

$$\hat{w}_1 = 1 + 1.5[-\Delta P_\gamma]^+ - 0.7[-\Delta P_z]^+ \quad (16)$$

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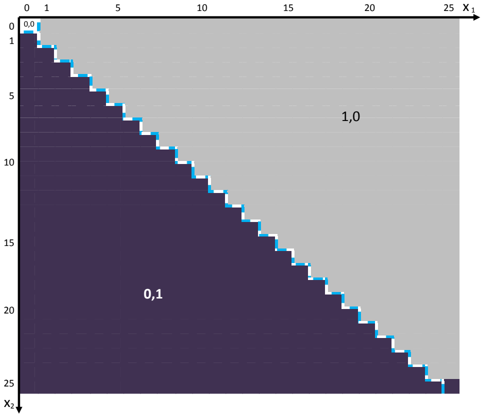
- where, $\Delta P_\gamma = P(\gamma_1 = 1) - P(\gamma_2 = 1)$
- and $\Delta P_z = P(z_1 = u) - P(z_2 = u)$.

Heuristic (dotted line) vs. optimal policy; $c = 15$



$\alpha_i = \beta_i = p$ for all $0 \leq p \leq 1$ and $P(z_i = 5) = 0.5$ for all $i \in \{1, 2\}$.

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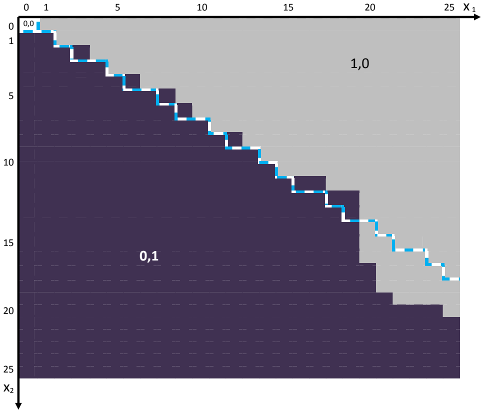

$P(\gamma_1 = 1) = 0.8$ and $P(\gamma_2 = 1) = 0.5$ and $P(z_i = 5) = 0.5$.

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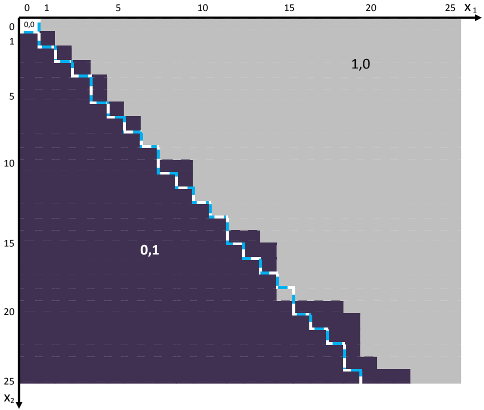

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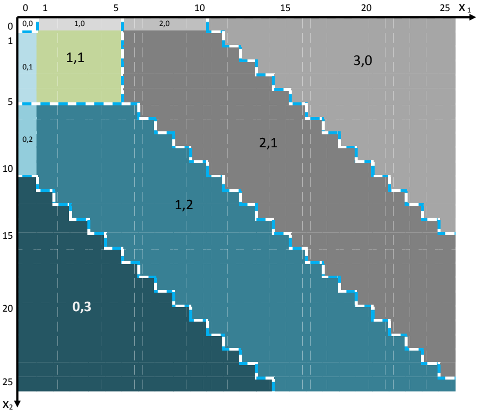
Heuristic (dotted line) vs. optimal policy; $c = 5$



$\alpha_i = \beta_i = p$ for all $0 \leq p \leq 1$ and $P(z_i = 5) = 0.5$ for all $i \in \{1, 2\}$.

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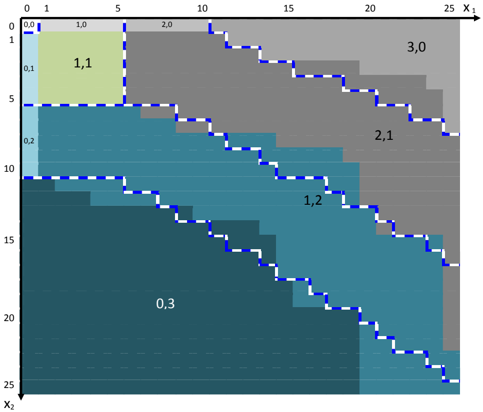

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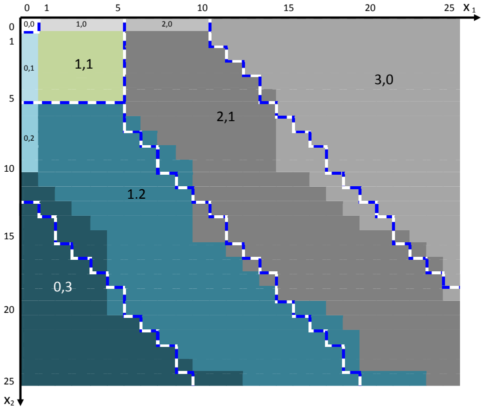

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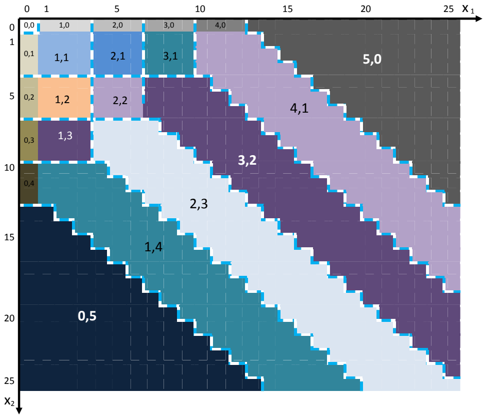
Heuristic (dotted line) vs. optimal policy; $c = 3$



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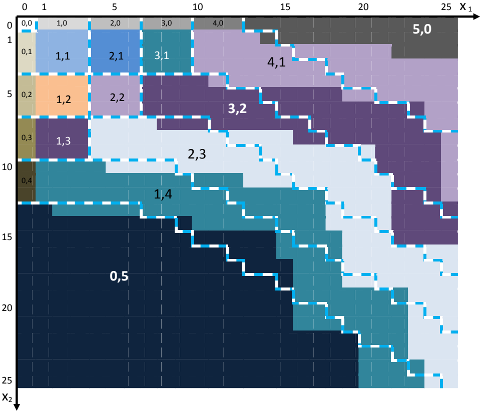

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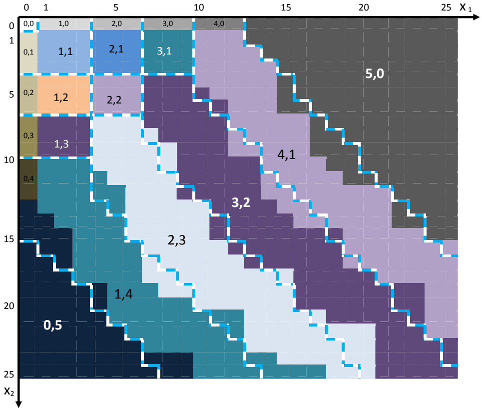

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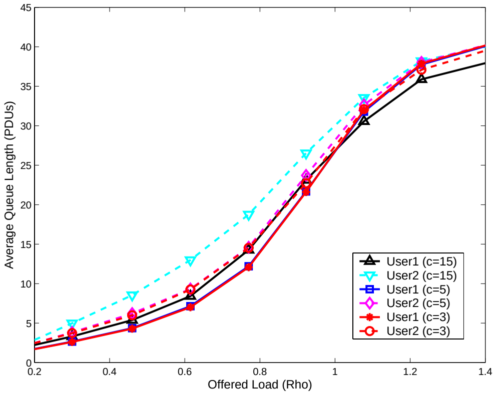
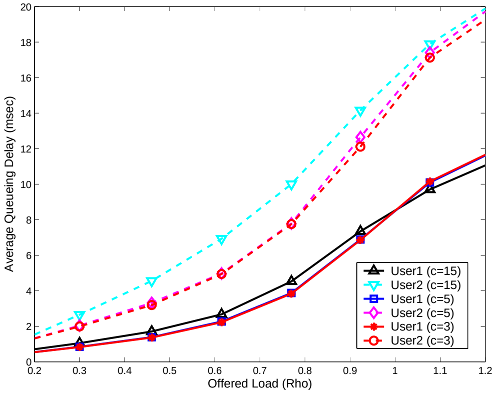
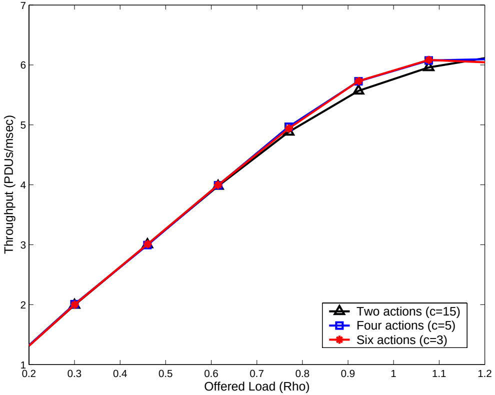
The Effect of Policy Granularity on Queue Length



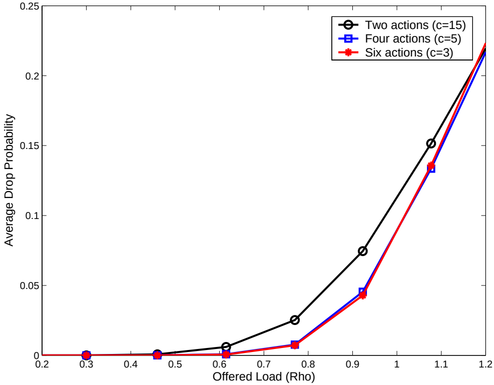
Effect of Policy Granularity on Ave. Queueing Delay



The Effect of Policy Granularity on Scheduler Throughput



The Effect of Policy Granularity on Dropping Probability



Heuristic Policy Evaluation

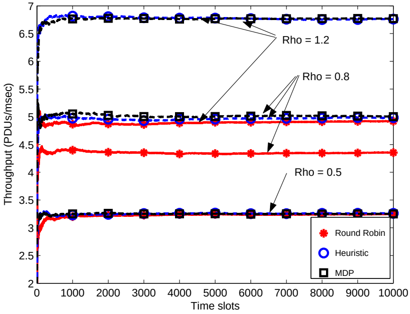


Figure: System throughput for different loading conditions.

Where $\rho = \sum_i P_{z_i} u_i / r^{\pi}$ is the offered load and r^{π} is the measured system capacity under the policy π.

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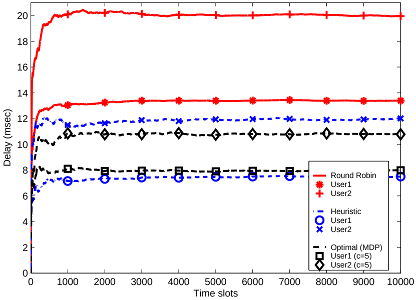

Figure: Queueing delay performance, $P(\gamma_1 = 1) = 0.84$, $P(\gamma_2 = 1) = 0.5$, $q_1 = 0.8$, $q_2 = 0.5$ and $u = 10$.

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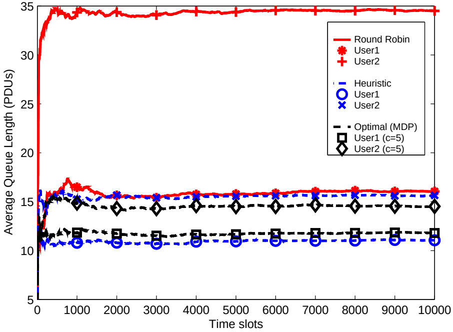

Figure: Queue length, $\rho = 0.75$, $P(\gamma_1 = 1) = 0.84$, $P(\gamma_2 = 1) = 0.5$, $q_1 = 0.5$, $q_2 = 0.5$ and $u = 10$.

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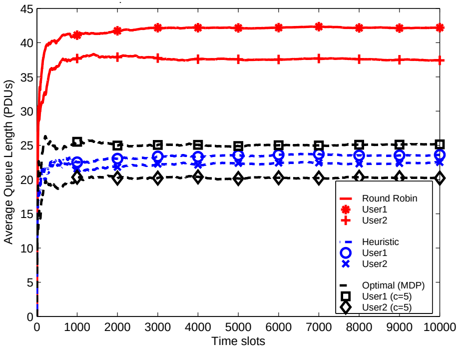

Figure: Queue length, $\rho = 1.0$, $P(\gamma_1 = 1) = 0.84$, $P(\gamma_2 = 1) = 0.5$, $q_1 = 0.8$, $q_2 = 0.5$ and $u = 10$.

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- However, the performance gain when using $c < 5$ is marginal and does not justify the added complexity.

Conclusion cont.

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- The performance of the resulted heuristic policy matches very closely to the optimal policy.
- The results also proved that RR is undesirable in HSDPA system due to the poor performance and lack of fairness.
- The suggested heuristic policy can be extended to the case with more than two active users. It also can be easily adapted to accommodate more than one class of service.

Future Work

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- Using the proposed model to study a system with 3-state FSMC or higher.
- Relax the assumption of error free transmission and extend the model to take into account retransmissions.
- Study the effect of using different arrival process statistics using simulation obviously.

Future Work cont.

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- Evaluate the Heuristic policy by finding the value function when using the heuristic policy as input and compare it to the value function we obtained from value iteration.
- Prove analytically some of the optimal policy and value function characteristics, such as monotonicity, multi-modularity, and the switch-over behavior that we noticed before.

Thank You

Discussion

Acronyms

- HSDPA–High Speed Downlink Packet Access.
- 3GPP–Third Generation Partnership Project
- MDP–Markov Decision Process
- TDMA–Time Division Multiple Access
- CDMA–Code Division Multiple Access
- TTI–Transmission Time Interval (2 ms)
- FSMC–Finite State Markov Channel
- SDU–Service Data Unit
- RLC–Radio Link Control Protocol located at Radio Network Controller (RNC)
- PDU–Protocol data unit
- LQF–Longest Queue First