Optimal Scheduling Policy Determination in HSDPA Networks

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- Optimal Transmission: Maximizes the overall cell throughput.
- Optimal Resource Utilization: Provide channel aware (diversity gain) and high speed resource allocation.

Motivation

- 3GPP only suggested some guidelines for HSDPA downlink scheduler and left the design specifics undefined.
- 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.

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- Define an *objective function*.
- Value iteration is then used to solve for optimal policy.
- Study the structure of the optimal policy and develop a near-optimal heuristic policy.

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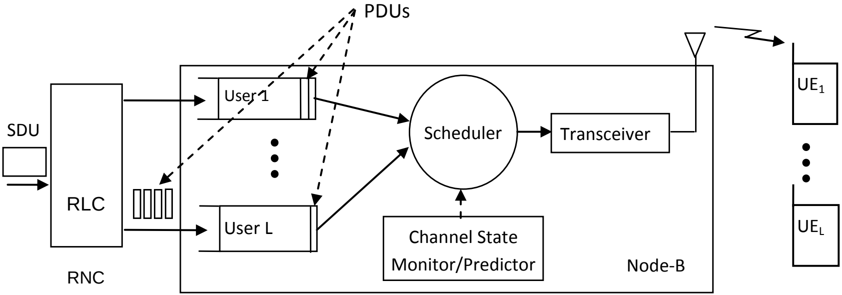
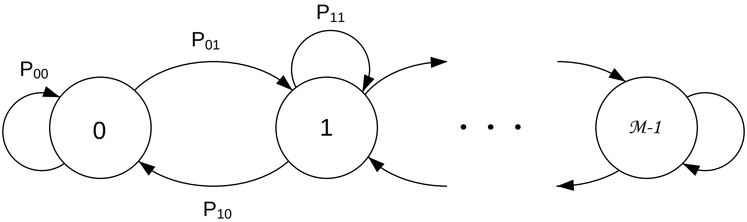
- Time is slotted into fixed length 2 ms TTIs.
- During each TTI, there are 15 available codes that may be allocated to one or more users.

HSDPA Scheduler Model (Downlink)



FSMC Model for HSDPA Downlink Channel



The Model

- MDP based Model.
- HSDPA downlink scheduler is modelled by the 5-tuple $(T, S, A, P_{\mathbf{ss}'}(\mathbf{a}), R(\mathbf{s}, \mathbf{a}))$,
  where,
  - T is the set of decision epochs,
  - S and A are the state and action spaces,
  - $P_{\mathbf{ss}'}(\mathbf{a}) = Pr(\mathbf{s}(t+1) = \mathbf{s}' | \mathbf{s}(t) = \mathbf{s}, \mathbf{a}(\mathbf{s}) = \mathbf{a})$ is the state transition probability, and
  - $R(\mathbf{s}, \mathbf{a})$ is the immediate reward when at state $\mathbf{s}$ and taking action $\mathbf{a}$.

Basic Assumptions

- L active users in the cell.
- Finite buffer with size B per user for each of the L users.
- Error free transmission.
- SDUs are segmented by RLC into a fixed number of PDUs (u_i) and delivered to Node-B at the beginning of the next TTI.
- Independent Bernoulli arrivals with parameter q_i.
- Scheduler can assign c codes chunks at a time, where $c \in \{1, 3, 5, 15\}$.

Basic Assumptions–FSMC State Space

- The channel state of user i during slot t is denoted by $\gamma_i(t)$.
- Channel state space is the set $\mathcal{M} = \{0, 1, \ldots, M-1\}$.
- user i channel can handle up to $\gamma_i(t)$ PDUs per code.

State and Action Sets

- The system state $\mathbf{s}(t) \in S$ is a vector and is given by

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

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  - subject to,

$$\sum_{i=1}^{L} a_i(\mathbf{s}) \leq \frac{15}{c}, \quad and \quad a_i(\mathbf{s}) \leq \left\lceil \frac{x_i(t)}{\gamma_i(t) c} \right\rceil$$

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  - $a_i(t)c$, number of codes allocated to user i at time epoch t.

Reward Function

- The reward must achieve the **objective function**
- $R(\mathbf{s}, \mathbf{a})$ have two components corresponding to the two objectives

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

where we defined the **fairness factor** (σ) to reflect the significance of fairness in the optimal policy.

- The positive term of the reward maximizes the cell throughput.
- The second term guarantees some level of fairness and reduces dropping probability.

State Transition Probability

- $P_{\mathbf{ss}'}(\mathbf{a})$ denotes the probability that choosing an action $\mathbf{a}$ at time t when in state $\mathbf{s}$ will lead to state $\mathbf{s}'$ at time $t+1$.

$$\begin{aligned} P_{\mathbf{ss}'}(\mathbf{a}) &= Pr(\mathbf{s}(t+1) = \mathbf{s}' | \mathbf{s}(t) = \mathbf{s}, \mathbf{a}(t) = \mathbf{a}) \\ &= Pr(x'_1, \ldots, x'_L, \gamma'_1, \ldots, \gamma'_L | x_1, \ldots, x_L, \gamma_1, \ldots, \gamma_L, a_1, \ldots, a_L) \end{aligned}$$

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- The evolution of the queue size (x_i) is given by

$$\begin{aligned} x_i' &= \min\left([x_i - y_i]^+ + z_i', B\right) \\ &= \min\left([x_i - a_i\gamma_i c]^+ + z_i', B\right) \end{aligned} \quad (4)$$

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- Using the independence of the channel state and queue sizes

$$P_{\mathbf{ss}'}(\mathbf{a}) = \prod_{i=1}^{L} \left(P_{x_i x'_i}(\gamma_i, a_i)\, P_{\gamma_i \gamma'_i} \right) \quad (5)$$

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

State Transition Probability cont.

$$P_{x_i x_i'}(\gamma_i, a_i) = \begin{cases} 1 & \text{if } x_i' = x_i = B \ \& \ a_i\gamma_i = 0, \\ q_i & \text{if } x_i' = x_i = B \ \& \ 0 < a_i\gamma_i c \leq u_i, \\ q_i & \text{if } x_i' = B \ \& \ x_i < B \ \& \ W1 \geq B, \\ q_i & \text{if } x_i' < B \ \& \ x_i' = W1, \\ 1 - q_i & \text{if } x_i' < B \ \& \ x_i' = W2, \\ 0 & \text{otherwise.} \end{cases} \quad (6)$$

where

$$W1 = [x_i - a_i\gamma_i c]^+ + u_i$$
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- The optimal policy is characterized by

$$V^*(\mathbf{s}) = \max_{\mathbf{a} \in A} [R(\mathbf{s}, \mathbf{a}) + \lambda \sum_{\mathbf{s}' \in S} P_{\mathbf{s}\mathbf{s}'}(\mathbf{a}) V^*(\mathbf{s}')] \tag{7}$$

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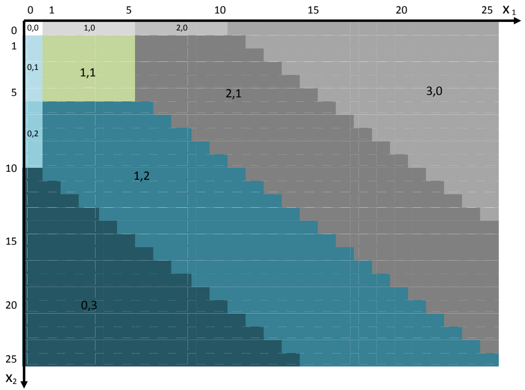
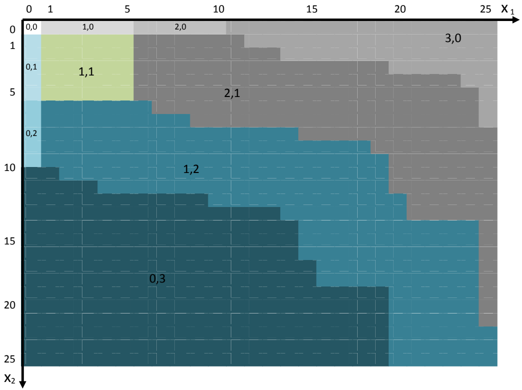
  where, $V^*(\mathbf{s}) = \sup_{\pi} V^{\pi}(\mathbf{s})$, attained when applying the optimal policy π^*.
- The model was solved numerically using **Value Iteration**.

The Optimal Policy for Two Symmetrical Users



$P(\gamma_i=1)=0.5$ and $P(z_i=5)=0.5$ for all $i \in \{1,2\}$; $c = 5$.

The Effect of Channel Quality on Policy Structure



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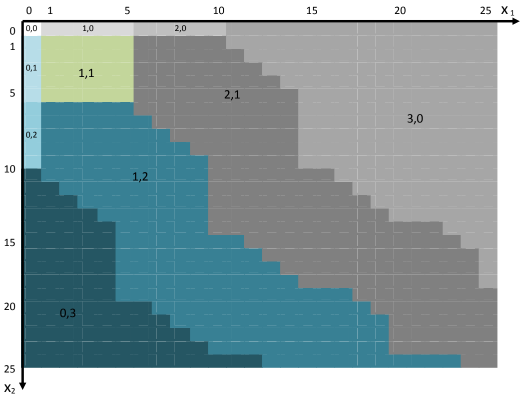
The Effect of Arrival Probability on Policy Structure



$P(\gamma_1 = 1) = P(\gamma_2 = 1) = 0.5$ and $P(z_1\!=\!5)\!=\!0.8$ $P(z_2\!=\!5)\!=\!0.5.$

Heuristic Policy

We studied the optimal policy structure by running a wide range of scenarios, we noticed the following trends

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- $f()$ is increasing in $|\Delta P_\gamma|$ and decreasing in $|\Delta P_z|$.

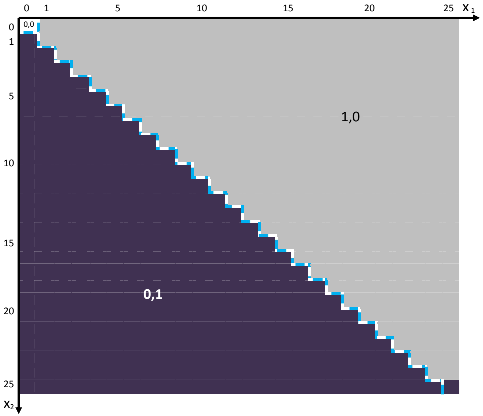
Weight Function Approximation

Following these observations, we approximated w_1 and w_2 as follows

$$\hat{w}_1 = 1 + 1.5[-\Delta P_\gamma]^+ - 0.7[-\Delta P_z]^+ \quad (10)$$

$$\hat{w}_2 = 1 + 1.5[\Delta P_\gamma]^+ - 0.7[\Delta P_z]^+ \quad (11)$$

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



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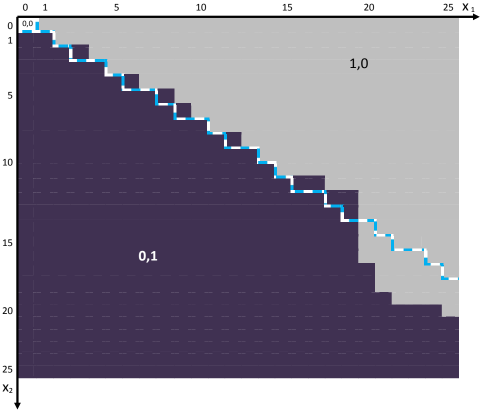

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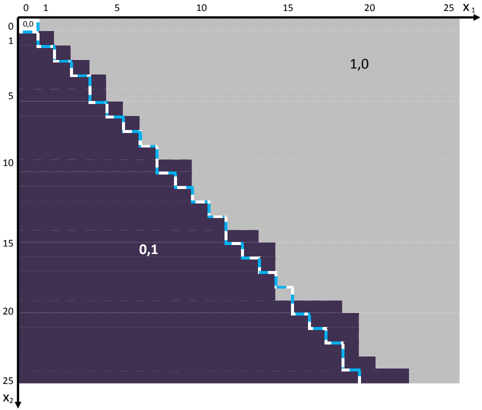

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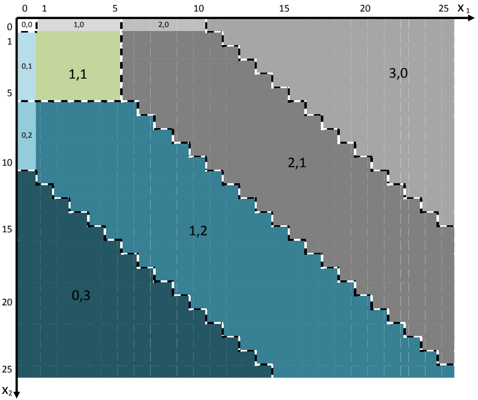

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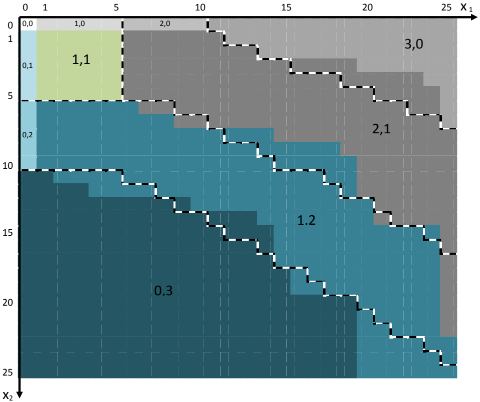

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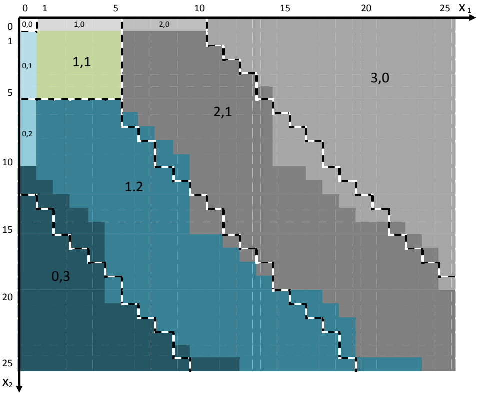

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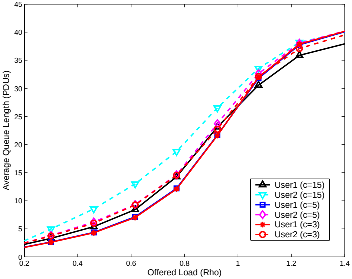
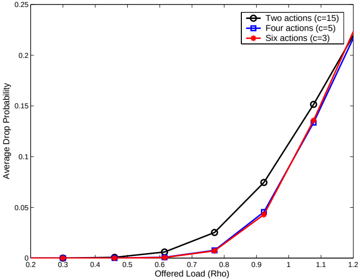
Performance Evaluation: The Effect of Policy Granularity



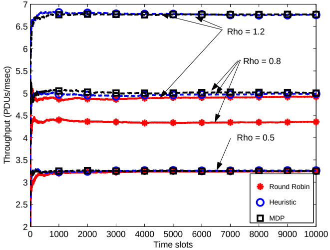
(a) on Average Queue Length



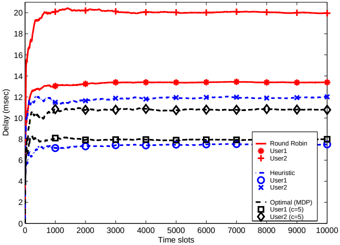
(b) on Average Drop Probability

Where $\rho = \sum_i P_{z_i} u_i / r^\pi$ is the offered load and r^π is the measured system capacity under π. $P(\gamma_1 = 1) = 0.8$ and $P(\gamma_2 = 1) = 0.5$.

Heuristic Policy Evaluation



(c) System Throughput for different ρ; $P(\gamma_1=1)=0.8$ and $P(\gamma_2=1)=0.5$.



(d) Queueing Delay Performance; $P(\gamma_2 = 1) = 0.5$, $q_1 = 0.8$, $q_2 = 0.5$ and $u = 10$.

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- A policy with finer granularity will perform better in light to moderate loading conditions, while a coarse policy is more desirable in heavy loading conditions.
- However, the performance gain when using $c < 5$ is marginal and does not justify the added complexity.

Conclusion cont.

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- 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.

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- Study the effect of using different arrival process statistics using simulation obviously.

Thank You

Discussion

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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