Downlink Scheduler Optimization in High-Speed Downlink Packet Access Networks

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2 Methodology

3 Problem Definition and Model Description

4 Case Study and Results

5 Conclusion and Future Work

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

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- Value iteration is then used to solve for optimal policy.

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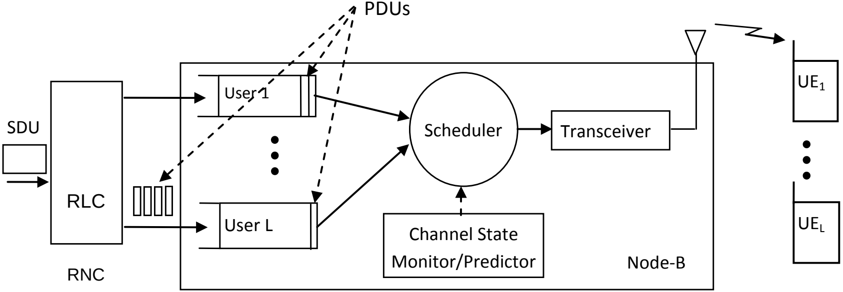
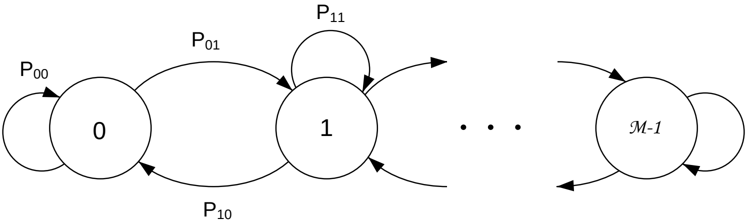
- Time is slotted into fixed length 2 ms TTIs.
- During each TTI, there are 15 available codes that may be allocated to one or more users.

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

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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

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

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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$$= Pr(x'_1,\ldots,x'_L,\gamma'_1,\ldots,\gamma'_L|x_1,\ldots,x_L,\gamma_1,\ldots,\gamma_L,a_1,\ldots,a_L)$$

- 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

$$W1 = [x_i - a_i\gamma_i c]^+ + u_i$$
$$W2 = [x_i - a_i\gamma_i c]^+$$

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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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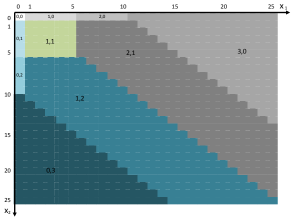
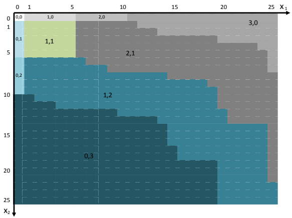
- The model was solved numerically using **Value Iteration**.

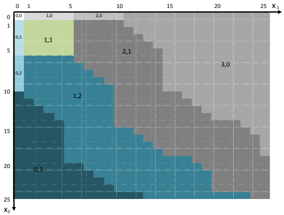
The Optimal Policy Structure



(a) Symmetrical case



(b) $P_{\gamma_1} = 0.8$, $P_{\gamma_2} = 0.5$.



(c) $P(z_1 = 5) = 0.8$ and $P(z_2 = 5) = 0.5$.

The Optimal Policy for Two Symmetrical Users, Different Channel Quality, Different Arrival Probability

Heuristic Policy

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- The weight (w_i) is a function of the difference of the two channel qualities and that of the arrival probabilities:

$$w_1 = f([-\Delta P_\gamma]^+, [-\Delta P_z]^+) \quad (8)$$

$$w_2 = f([\Delta P_\gamma]^+, [\Delta P_z]^+) \quad (9)$$

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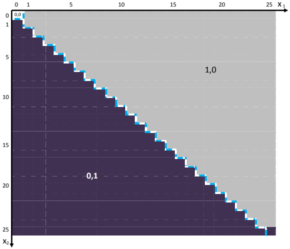
- $f()$ is increasing in $|\Delta P_\gamma|$ and decreasing in $|\Delta P_z|$.

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



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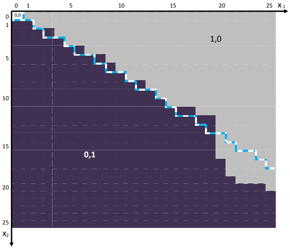

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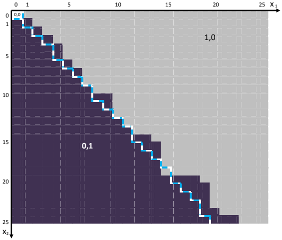
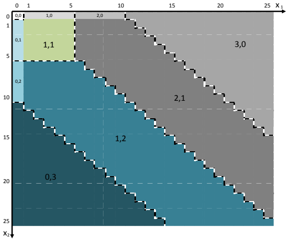


(f) $P(z_1 = 5) = 0.8$ and $P(z_2 = 5) = 0.5$

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



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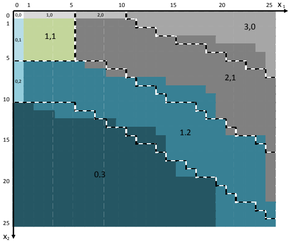

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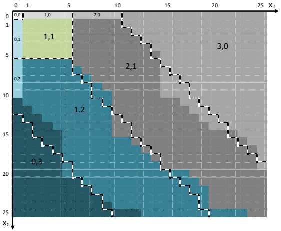

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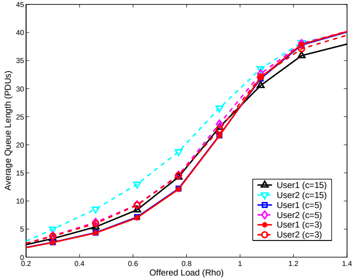
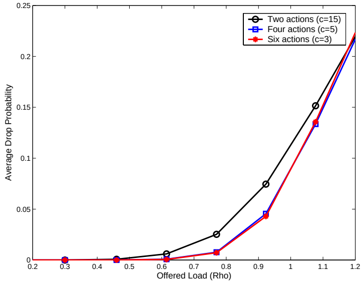
Performance Evaluation: The Effect of Policy Granularity



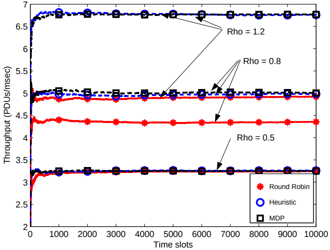
(j) on Average Queue Length



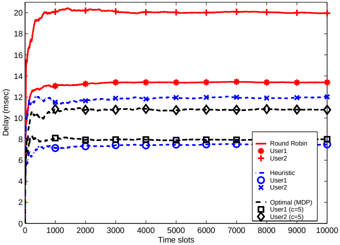
(k) on Average Drop Probability

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



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



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

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- The suggested heuristic policy has a reduced constant time complexity ($O(1)$) as compared to the exponential time complexity needed in the determination of the optimal policy.
- 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.

Contributions

1. A novel approach and a methodology for scheduling in HSDPA system were developed.
2. The HSDPA downlink scheduler was modeled by MDP, then Dynamic Programming is used to find the optimal code allocation policy in each TTI (refer to [1] and [2]).
3. A heuristic approach was developed and used to find the near-optimal heuristic policy for the 2-user case. This work was presented in [3].
4. An optimal policy for code allocation in HSDPA system using FSMC was investigated and the optimal policy structure and the effect of the increased number of channel model states on the optimal policy structure and model accuracy was studied and presented in [4].
5. An extension of the heuristic approach for any finite number of users was derived analytically, using the information about the optimal policy structure and Order Theory, and presented in [5].
6. An analytic model was developed, using stochastic modeling, to find the average service rate and server share allocation policy for a group

Future Work

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- Relax the assumption of error free transmission and extend the model to take into account retransmissions.

Future Work

- 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.
- 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.

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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