



# A CHANNEL PREDICTIVE PROPORTIONAL FAIR SCHEDULING ALGORITHM

Hans Jørgen Bang,  
Torbjörn Ekman, David Gesbert  
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# Overview



- Introduction
- Proportional Fair Scheduling
- Predictive Scheduling
  - Iterative algorithm
- Simulations
  - Fairness measure
- Conclusion



# Introduction

- Multi-user diversity scheduling
  - The supported rates for each user vary
  - Schedule to increase system throughput
- Channel prediction
  - Future supported rates can be estimated
- Improved throughput-fairness trade-off



# Throughput-fairness trade-off

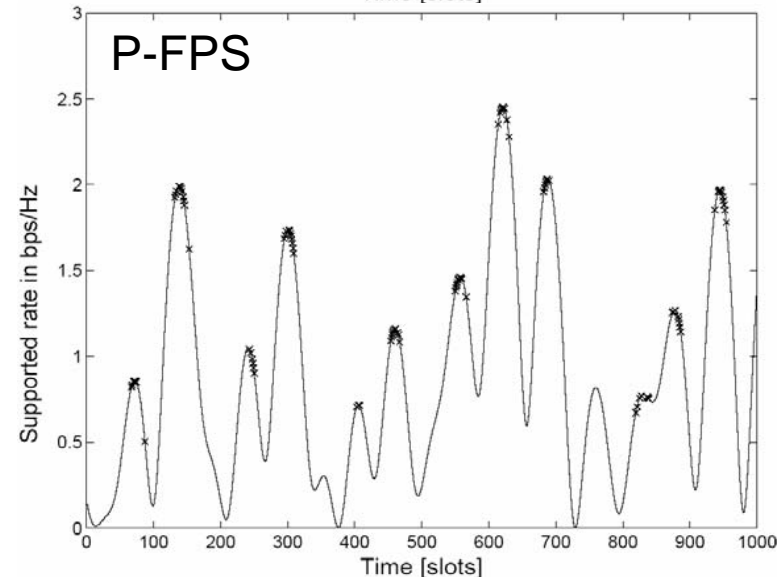
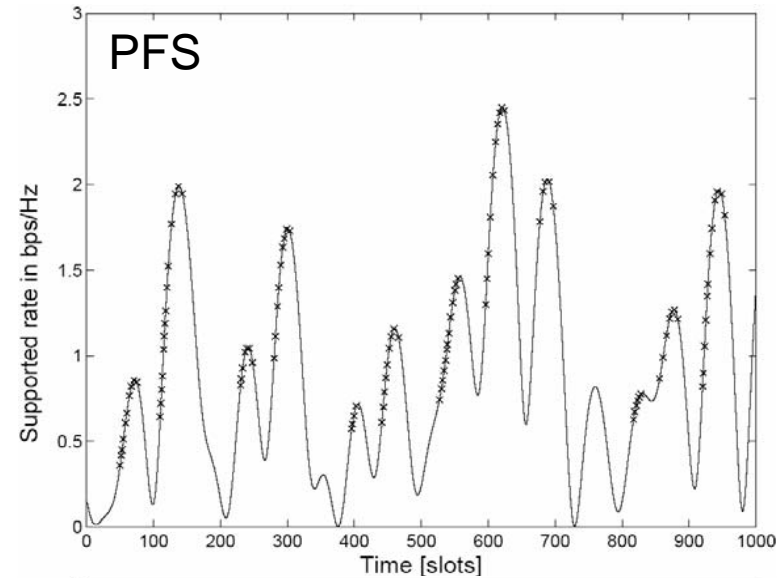
- Fundamental trade-off between total cell throughput and fairness
- Max SNR scheduling
  - Max throughput
  - Relies only on the current channel state
  - Fair over infinite time horizon for equal channel statistics (otherwise normalized max SNR scheduling)
- Tighter fairness constraints
  - Leads to reduced throughput
  - Gains can be obtained by using fading predictions

# A Qualitative Comparison

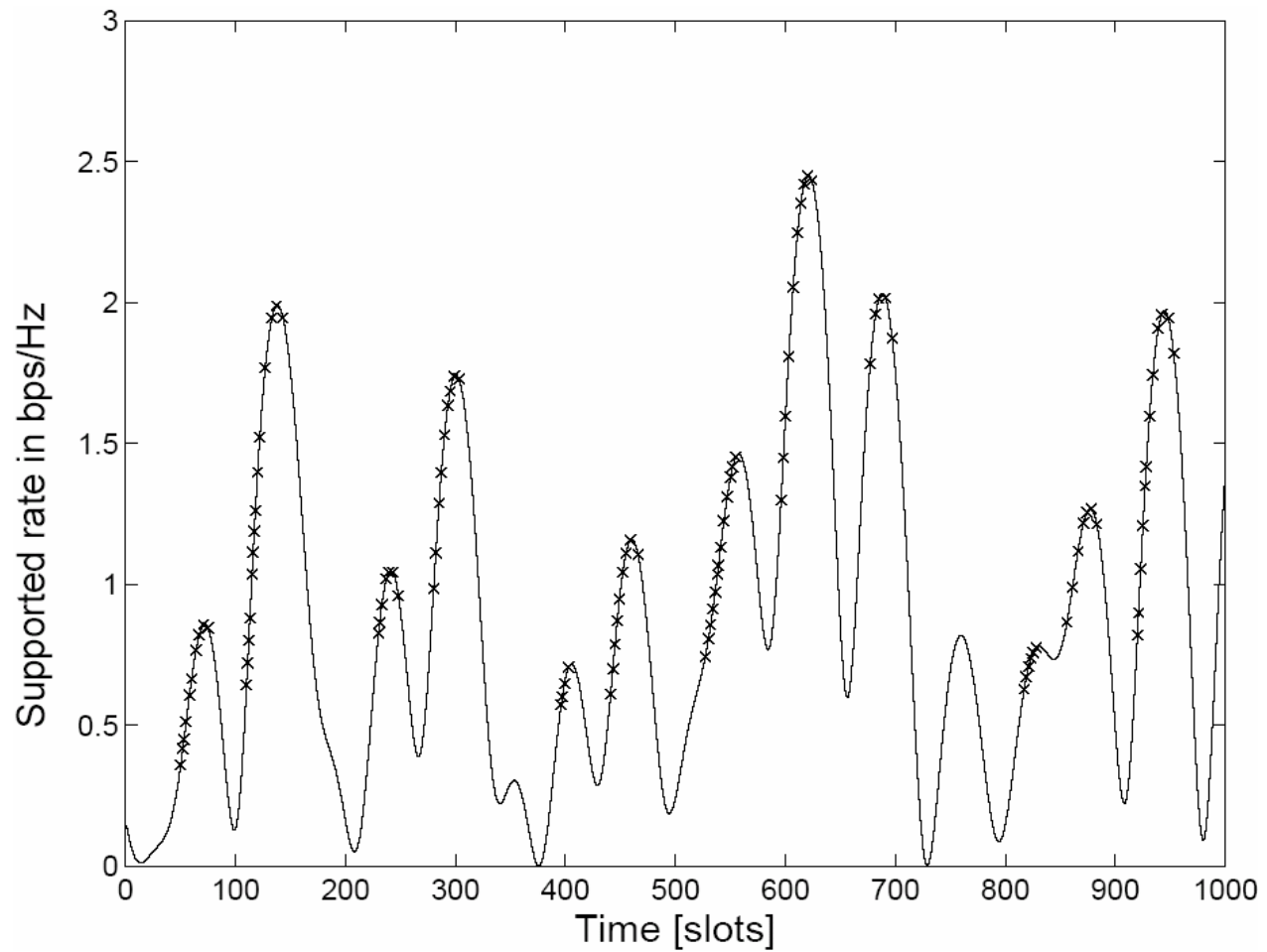
- Proportional Fair Scheduling (PFS) v.s. Predictive PFS
- Scheduling around the peaks instead for on the flanks.
- Improved throughput

## Simulation

- Ten users with equal channel statistics
- Average SNR 0dB
- Time slot Doppler frequency product 0.01
- Prediction 20 time slots ahead
- The supported rate and scheduling instances for one user

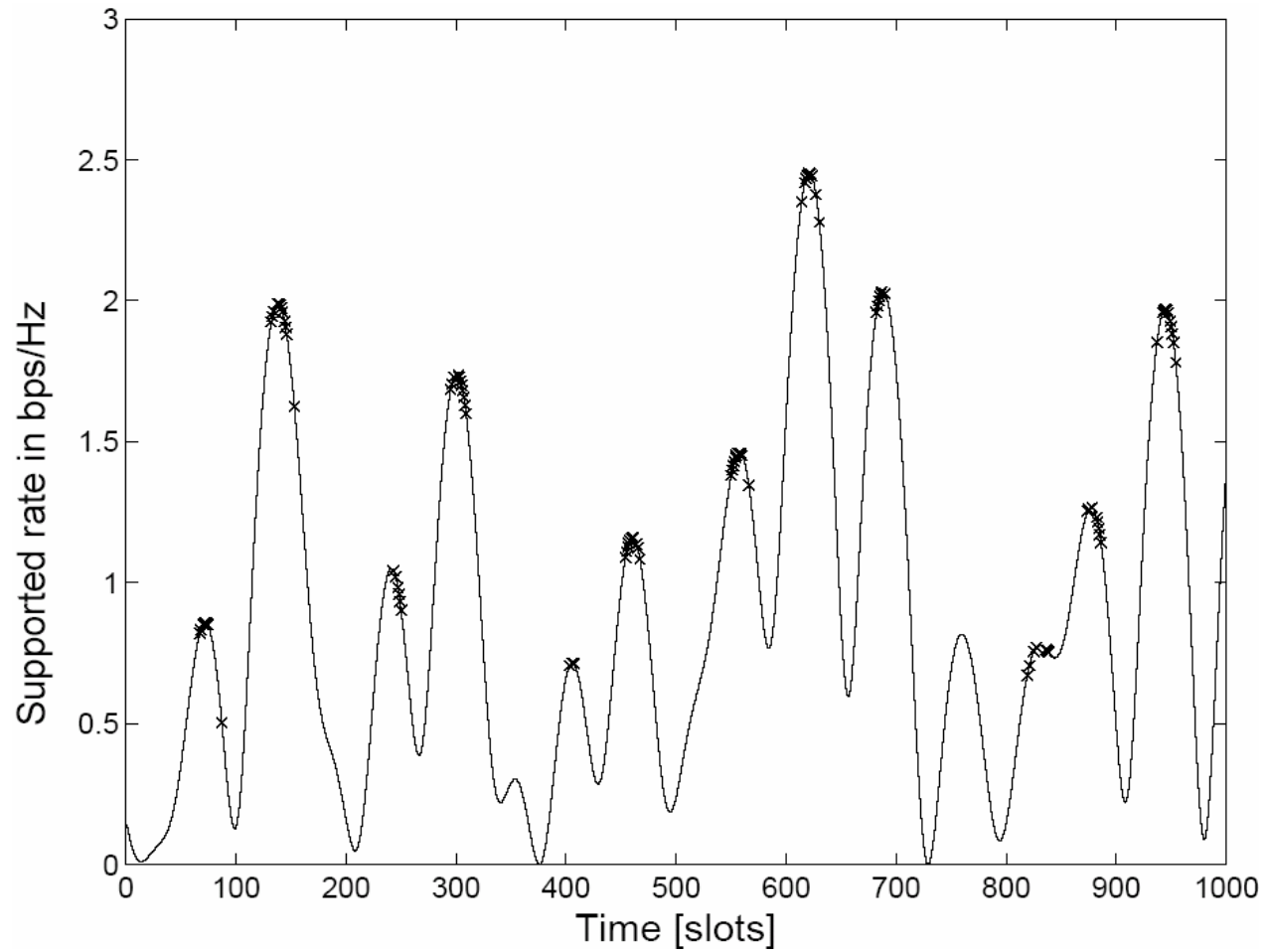


# PFS





# P-PFS





# Proportional Fair Scheduling

- Pick the user with the highest ratio between **rate** and **local accumulated throughput** in the next time slot

$$i^*(k) = \arg \max_{i=1,..,N} \frac{R_i(k)}{T_i(k)}$$

- Optimized system utility function  
Sum of the log of the local throughputs

$$U(k) = \sum_{j=1}^N \log T_j(k)$$

- Exponential window for local accumulated throughput (time constant  $t_c$ )

$$T_i(k+1) = \begin{cases} \left(1 - \frac{1}{t_c}\right) T_i(k) + \frac{1}{t_c} R_i(k) & i = i^*(k) \\ \left(1 - \frac{1}{t_c}\right) T_i(k) & i \neq i^*(k) \end{cases}$$





# Predictive Proportional Fair Scheduling (P-PFS)

- In time slot  $k$ :  
don't maximize  $U(k+1)$ , maximize  $U(k+L)$
- Scheduling vector  $\mathbf{i}(k) = (i_1, i_2, \dots, i_L)$
- Schedule to maximize  $U(k+L)$   
$$\mathbf{i}^*(k) = \arg \max_{\mathbf{i} \in \mathcal{F}} \hat{U}(k+L | \mathbf{i})$$
- The estimated future system utility function  $U(k+L)$ , assuming user  $i_l$  is served in slot  $k+l-1$  is  $\hat{U}(k+L | (i_1, i_2, \dots, i_L))$



# Problems With Predictive Scheduling

- Future supported data rates are assumed known
  - Short range channel state predictions are good
  - Long rang predictions are quite poor
  - Don't schedule too far
  - Don't trust your schedule:  
Redo scheduling in each time step
- Full search of scheduling vectors to maximize a system utility function is computational demanding
  - Use possibly suboptimal iterative solutions



# Cope With Prediction Uncertainty: Always Redo Scheduling!

$k$	$k+1$		$k+L-2$	$k+L-1$	Time step
$R_1(k/k-1)$	$R_1(k+1/k-1)$	...	$R_1(k+L-2/k-1)$	$R_1(k+L-1/k-1)$	Rate prediction quality decrease with increasing prediction range
$R_2(k/k-1)$	$R_2(k+1/k-1)$	...	$R_2(k+L-2/k-1)$	$R_2(k+L-1/k-1)$	
$R_N(k/k-1)$	$R_N(k+1/k-1)$	...	$R_N(k+L-2/k-1)$	$R_N(k+L-1/k-1)$	
$i_1(k)$	$i_2(k)$	...	$i_{L-1}(k)$	$i_L(k)$	Scheduling vector

**Only effectuate the first component of the scheduling vector**

New channel state information. **Update rate predictions**

**Next time step**

$R_1(k+1/k)$	$R_1(k+2/k)$	...	$R_1(k+L-1/k)$	$R_1(k+L/k)$
$R_2(k+1/k)$	$R_2(k+2/k)$	...	$R_2(k+L-1/k)$	$R_2(k+L/k)$
$R_N(k+1/k)$	$R_N(k+2/k)$	...	$R_N(k+L-1/k)$	$R_N(k+L/k)$
$i_1(k+1)$	$i_2(k+1)$	...	$i_{L-1}(k+1)$	$i_L(k+1)$

Redo scheduling



# Cope With Complexity: Iterative Search!

$i_1(k-1)$	$i_2(k-1)$	...	$i_{L-1}(k-1)$	$i_L(k-1)$	$= \mathbf{i}(k-1)$ Previous scheduling vector
$i_2(k-1)$	$i_3(k-1)$	...	$i_L(k-1)$	1	$= \mathbf{i}^0(k)$ Initialization
$i_2(k-1)$	$i_3(k-1)$	...	$i_L(k-1)$	$i_L^1(k)$	$= \mathbf{i}^1(k)$ First iteration
$i_2(k-1)$	$i_3(k-1)$	...	$i_{L-1}^2(k)$	$i_L^1(k)$	$= \mathbf{i}^2(k)$ Second iteration
⋮					
$i_1^L(k)$	$i_2^{L-1}(k)$	...	$i_{L-1}^2(k)$	$i_L^1(k)$	$= \mathbf{i}^L(k)$ $L$ :th iteration
$i_1^L(k)$	$i_2^{L-1}(k)$	...	$i_{L-1}^2(k)$	$i_L^{L+1}(k)$	$= \mathbf{i}^{L+1}(k)$ $L+1$ :th iteration

Keep iterating until it converges

Each iteration one component of the vector is recomputed,  
all the others are held fixed

$$i_l^{n+1}(k) = \arg \max_{i=1, \dots, N} \hat{U}(k + L | \mathbf{i}^n(k) \stackrel{l}{\leftarrow} i)$$



# Some Comments on the Algorithm

In the proposed frame work

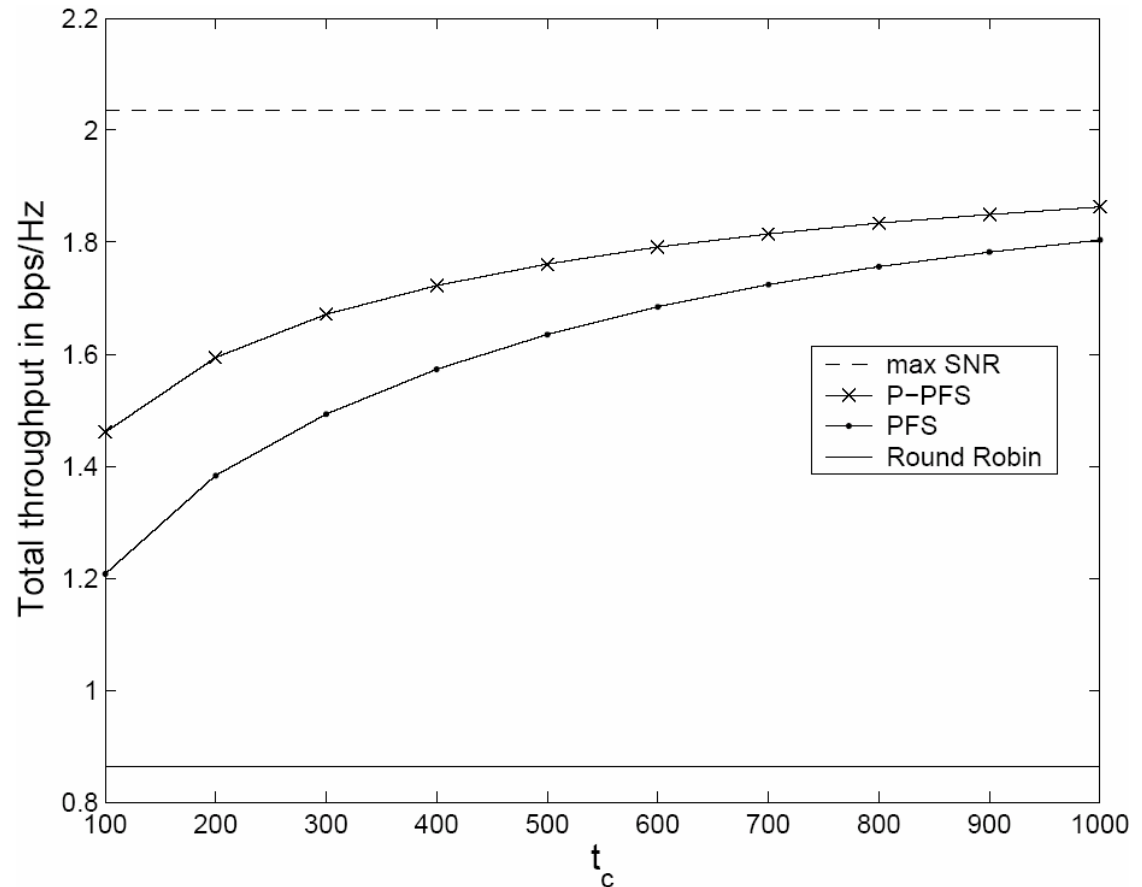
- Any rate predictor can be used
  - It should be conservative
- Any utility function  $U$  can be used
  - Here a generalization of PFS leads to maximizing  $U(k+L)$ .
  - It is feasible to redefine  $U$  to instead maximize  $U(k+1)$  taking past and future rates into account
- The iterations converge fast
  - A small amount of new channel state information is introduced at each time step
  - The initial scheduling vector is based on a vector obtaining a maximum in the previous time step



# Prediction Leads to Higher Throughput

## Simulation

- 15 users
- Equal channel statistics
- Average SNR 0dB
- Time slot Doppler frequency product 0.01
- Prediction range: 10 slots





# How to Measure Fairness

- Jain's fairness index
- Measures spread of the users average throughput (rectangular window)
- $J=1$  absolute fairness
- $J=1/N$  totally unfair (all resources to one user)
- $N$  is the number of users

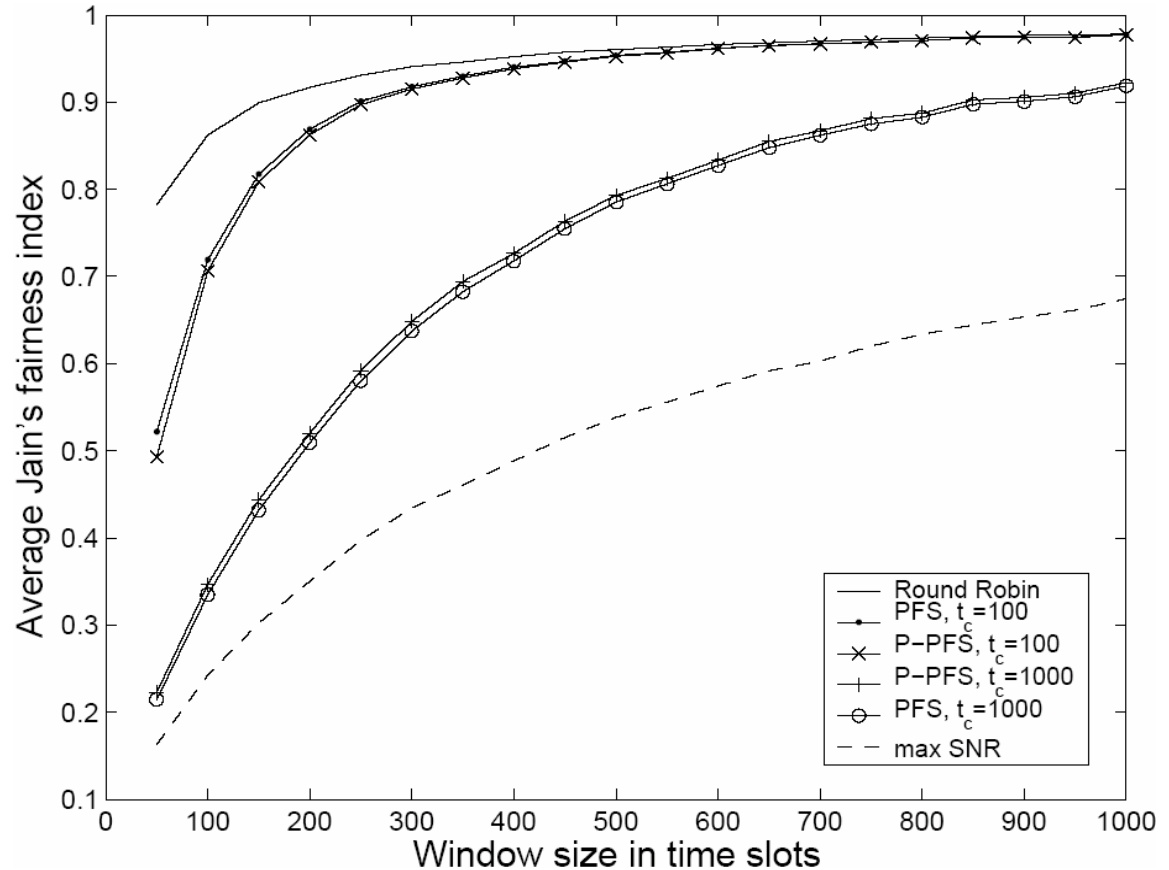
$$J = \frac{\left(\sum_{i=1}^N T_i\right)^2}{N \sum_{i=1}^N T_i^2}$$



# Exploiting predictions doesn't compromise fairness

## Simulation

- 15 users
- Equal channel statistics
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# Conclusion

- Introduced a wireless scheduling algorithm
- Exploiting fading predictions in a robust manner
- Reasonable increase in complexity
- Increased throughput without compromising fairness
  
- This activity will be continued within the MoPSAR project