This document provides numerical results that support the theoretical findings in [1].

The authors in [1] deal with the efficient design of wireless networks by implementing cross-layer algorithms that exploit channel state information. More specifically, capitalizing on convex optimization and stochastic approximation tools, [1] develops a stochastic algorithm that allocates resources at network, link, and physical layers so that a sum-utility of the average end-to-end rates is maximized. Focus is placed on networks where interference is strong and nodes transmit orthogonally over a set of parallel channels. Convergence of the developed stochastic schemes is characterized, and the average queue delays are obtained in closed form.

Numerical results are presented for an any-to-any wireless network where all users are connected is considered. For simplicity we set the number of nodes to 3 and the number of channels to 5. Channels’ SNR are exponentially distributed and their average is 5dB. We consider 3 different flows, one for each possible destination. The utility to be maximized is $U_{i,f} = \log(1/10 + x)$ if $(i,f) = (1,3), (i,f) = (2,1)$ or $(i,f) = (2,2)$ while zero for all other node-flow combination. The average transmit power per node is 0.6 for nodes 1 and 2 and 0.55 for node 3. The stepsize for the stochastic updates is $\mu = 3 \cdot 10^{-4}$.

![Sample Av. Arrivals](image1)

![Sample Av. Powers](image2)

Figure 1 shows the time-evolution of the average power for each node (top) and average arrival rate (bottom) for each node and flow. Specifically, solid lines represent $\hat{\bar{p}}_i(n) = \frac{1}{n} \sum_{r=1}^{n} p_i[r]$ and $\hat{\bar{a}}_i^f(n) = \frac{1}{n} \sum_{r=1}^{n} a_i^f[r]$ while dotted lines are the...
values obtained from the optimal off-line solution (assuming perfect knowledge of the channel PDF). The results indicate that the proposed algorithm converges arbitrarily close to the optimal values (average flows with a non-zero utility are activated and power constraints are satisfied) in a finite number of iterations.

Results related to the queueing dynamics and delay are presented in Figure 2. In the first subplot solid lines represent $\hat{\rho}_i^f[n]$ while dotted lines are the optimal values $\rho_i^f$ obtained from the off-line solution. The second subplot represents the queues size for each user. For simplicity we only plot a small set of representative node-flow pairs. As expected, users with higher rate requirements have larger queues. On the other hand, comparing the trajectories of $q_i^f[n]$ and $\hat{\rho}_i^f[n]$ we verify the validity of the approximation $q_m[n] \cong \hat{\rho}_i^f[n]/\beta$. The third subplot, that represents the expected delay at every time instant, asserts the accuracy of the approximation in $\text{E:av_delay}$. Interestingly, simulations show that users with higher rate requirements, experience smaller delay, meaning that the algorithm “prioritizes” information of users with high rate demand.

References: