Resource Allocation Challenges in Future Wireless Networks

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Outline

General Introduction

- Future 5G cellular networks must support the 1000-fold increase in traffic demand
- New physical layer techniques, e.g. Massive MIMO, Millimeter wave (mmWave)
- New network architecture: user centric architecture
- Cloud RAN concept is also emerging
- Local caching of popular video traffic at devices and RAN edge
- Network topology
- Device-to-Device (D2D) communications

General Introduction

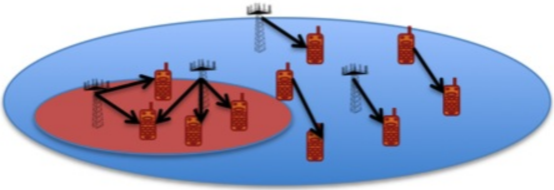

Figure: Wireless network

Resource Allocation in Wireless Networks

- Resource Allocation improves the network performance
- Resources: slots, channels, power, beamformers,...
- Services: voice, video streaming, interactive games, smart maps, ...
- Typical Utility functions: throughput, outage, packet error rate, transmit power,...
- Stability region

Resource Allocation in Wireless Networks

- Computational complexity: NP hard, sub-optimal solutions,...
- Physical layer (e.g. Massive MIMO): convex/non-convex, combinatorial, MINLP, ...optimization frameworks
- Non-existence of a central entity that can handle the allocation (e.g. D2D) and the amount of information exchange (signaling) between transmitters. Mathematical tools: stochastic game theory, distributed optimization, distributed learning, etc.
- Connectivity of the nodes (e.g. D2D communication).
- Network topology, high number of users
- Traffic pattern and QoS/QoE: stochastic constraints depending on the service used (real time, streaming, ...).
- Availability of the system state information (e.g. CSI).

Fully Decentralized Allocation

Fully Decentralized Policies

- Fully decentralized scenario
- No exchange of information between transmitters.
- Each transmitter exchanges information with its own receiver
- The action (resource) is a scalar
- Low complexity algorithm

Nash Equilibrium Seeking [1]

- Consider a network of n interacting nodes (e.g. interference)
- Each node has a reward to maximize. The decision of each node has an impact on the reward function of the other nodes.

$$\sup_{a_j \in \mathcal{A}_j} \mathbb{E}_{\mathbf{S}} r_j(\mathbf{S}, a_j, \mathbf{a}_{-j}) \quad j \in \mathcal{N} \tag{1}$$

where $\mathcal{N} := \{1, \ldots, N\}$ is the set of nodes, $\mathcal{A}_j \subseteq \mathbb{R}$ is the action space of node j, $\mathcal{S}$ is the state space of the whole system, where $\mathcal{S} \subseteq \mathbb{C}^{N \times N}$ and the node reward $r_j : \mathcal{S} \times \prod_{j' \in \mathcal{N}} \mathcal{A}_{j'} \longrightarrow \mathbb{R}$ is a smooth function. The state space $\mathcal{S}$ evolves ergodically such that $\mathbb{E}_{\mathbf{S}} r_j(\mathbf{S}, a_j, \mathbf{a}_{-j})$ is always finite.

Nash Equilibrium Seeking [1]

- No exchange of information between the transmitters
- Each receiver sends to its own transmitter a numerical value (or estimation) of the reward
- The reward may have a complicated expression (e.g. outage probability, throughput...) : computing the gradient is hard!
- Each transmitter has always an information to send (full buffer)
- Extremum seeking has been studied in [2, 3, 4, 5, 6, 7]

NE Seeking [1]

- Algorithm:

$$a_{j,k} = \hat{a}_{j,k} + b_j \sin(\Omega_j t_k + \phi_j) \quad (2)$$

$$\hat{a}_{j,k+1} = \hat{a}_{j,k} + \lambda_k z_j b_j \sin(\Omega_j t_k + \phi_j)\tilde{r}_{j,k+1} \quad (3)$$

- Performance:

Main Result (Variable Learning Rate)

The learning algorithm converges almost surely to the following ODE (i.e. asymptotic pseudo-trajectory):

$$\frac{d}{dt}\hat{a}_{j,t} = z_j b_j \sin(\Omega_j t + \phi_j)\mathbb{E}_{\mathbf{S}}[r_j(\mathbf{S}, \mathbf{a}_t)] \quad (4)$$

$$a_{j,t} = \hat{a}_{j,t} + b_j \sin(\Omega_j t + \phi_j) \quad (5)$$

NE Seeking [1]

Let $\Delta_t := \|\mathbf{a}_t - \mathbf{a}^*\|$ be the gap between the trajectory of the ODE $\mathbf{a}_t$ at time t and the equilibrium point $\mathbf{a}^*$.

Main Result (Exponential Stability)

There exist $M, T > 0$ and $\bar{\epsilon}, \bar{b}_j$ such that, for all $\epsilon \in (0, \bar{\epsilon})$ and $b_j \in (0, \bar{b}_j)$, if the initial gap is $\Delta_0 := \|\mathbf{a}^* - \mathbf{a}_0\|$ (which is small) then for all time t,

$$\Delta_t \leq y_{1,t} \tag{6}$$

where

$$y_{1,t} \quad := \quad Me^{-Tt}\Delta_0 + O(\epsilon + \max_j b_j^3) \tag{7}$$

Numerical Results [8]

- Power control problem (two users)

$$r_i(\mathbf{H}_k, \mathbf{p}_k) = w \log(1 + \frac{p_{i,k}|h_{ii,k}|^2}{\sigma^2 + \sum_{i' \neq i} p_{i',k}|h_{i'i,k}|^2}) - \kappa p_{i,k}$$

- $p_{1,0}$ and $p_{2,0}$: initial points
- $h_{i,j}$ is time varying, i.i.d. complex gaussian
- Noise variance $\sigma^2 = 1$
- NE: $p_i^* = 3.9604$ $i \in (1, 2)$

Numerical Results [8]

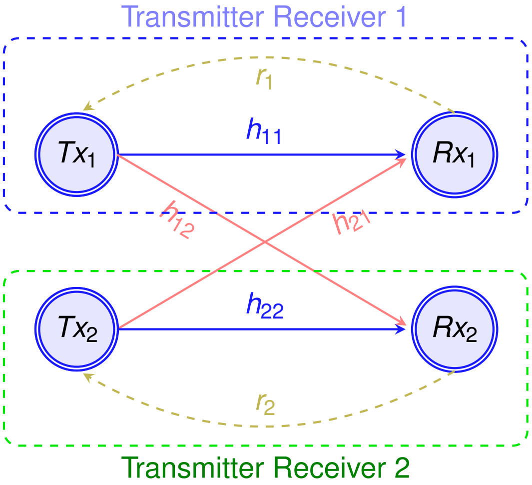

Figure: System model for two network each with transmit receive pair

Numerical Results [8]

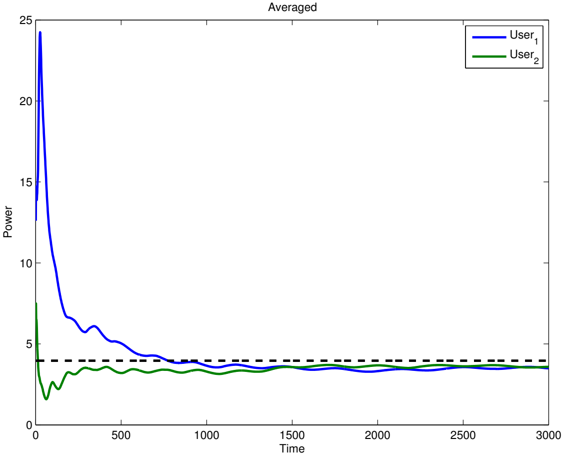

Figure: Power evolution (discrete time)

Randomized Policies

Randomized Policies

- Stability region
- SISO, MIMO : joint precoding and scheduling (queue aware)
- Joint resource allocation and channel feedback policies

Example [9]

- Two user interference channel with single antenna per user and fading channel
- $(R_1,0)$, (r_1,r_2) and $(0,R_2)$
- Symmetric environment ($r_1 = r_2 = \alpha$)
- FCSMA

$$\lambda < \frac{\alpha^2}{\alpha + 1} + \frac{1}{2(\alpha + 1)} \tag{8}$$

- Joint traffic splitting and FCSMA

$$\lambda < \frac{\alpha^2}{\alpha + \delta} + \frac{\delta}{2(\alpha + \delta)} \tag{9}$$

Future Work

- Dense networks
- Global convergence
- Network Stability and Feedback Design in Dense Networks
- Massive MIMO and dense networks (TDD)
- Stability region
- Decentralized stable solutions (joint precoding-scheduling)
- delay, QoS, QoE constraints

Last Slide

Thank you
Questions?

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