

Power Allocation in OFDMA Networks: An ADMM Approach

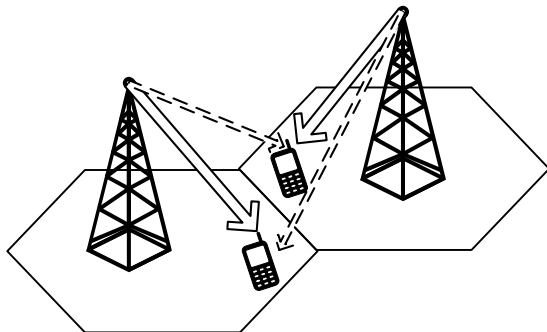
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Introduction

Considered OFDMA multicell wireless network

- Objective: increase throughput
- Obstacle: inter-cell interference
- One of possible solutions: dynamic resource management (scheduling and **power allocation**)



Problem Statement

Weighted sum rate maximization problem (**nonconvex**) [NCVX]:

$$\begin{aligned} \max_{\mathbf{0} \leq \mathbf{P} \leq \mathbf{S}_{max}} & \sum_{l=1}^L \sum_{n=1}^N w_{k(l,n)} \log(1 + \text{SINR}_{lk(l,n)}^n(\mathbf{P}^n)) \\ \text{s.t.} & \sum_{n=1}^N \mathbf{P}^n \leq \mathbf{P}_{max}, \end{aligned}$$

L – number of cells which share frequency resource divided by N blocks/frequency tones;

$k(l, n)$ – a user k is assigned to the n th frequency tone in the l th cell;

$w_{k(l,n)} > 0$ – users weights;

$\mathbf{P}_{max} \in \mathbb{R}^L$ and $\mathbf{S}_{max} \in \mathbb{R}^{NL}$

$\mathbf{P}^n = (P_1^n, \dots, P_L^n)^T \in \mathbb{R}^L$, P_l^n – DL transmit power spectral density;
Signal-to-interference-plus-noise ratio (SINR):

$$\text{SINR}_{lk(l,n)}^n(\mathbf{P}^n) = \frac{P_l^n G_{lk(l,n)}^n}{\sigma^2 + \sum_{j=1, j \neq l}^L P_j^n G_{jk(l,n)}^n}$$

$G_{jk(l,n)}^n = |h_{jk(l,n)}^n|^2$, $h_{jk(l,n)}^n$ is the channel response between base station j and user k in cell l in n frequency tone; σ^2 – noise;

Popular approaches to solve the considered nonconvex problem

- 1 dual decomposition
- 2 convex relaxation and dual decomposition

Pros and cons of dual decomposition

- + one problem is decomposed into N smaller problem
- isn't as robust as augmented Lagrangian methods

The two main ingredients of the proposed method are

- 1 successive convex relaxations based on SCALE approach
 - 2 Alternating Direction Method of Multipliers (ADMM) for solving obtained convex problems
- + ADMM has both separability and robustness

Convex relaxation based on SCALE approach

$$\alpha \log z + \beta \leq \log(1 + z), \quad \alpha = \frac{z_0}{1 + z_0}, \quad \beta = \log(1 + z_0) - \frac{z_0}{1 + z_0} \log z_0$$

Applying this inequality and transformation $\tilde{P}_l^n = \log(P_l^n)$ we get **convex** problem [SCALE]:

$$\begin{aligned} \max_{\tilde{\mathbf{P}} \leq \log(\mathbf{S}_{max})} \sum_{n=1}^N \phi_n(\tilde{\mathbf{P}}^n) &= \sum_{n=1}^N \sum_{l=1}^L w_{k(l,n)} \alpha_l^n \log(\text{SINR}_{lk(l,n)}^n(e^{\tilde{\mathbf{P}}^n})) \\ \text{s.t.} \quad \sum_{n=1}^N \exp(\tilde{\mathbf{P}}^n) &\leq \mathbf{P}_{max} \end{aligned}$$

Iteratively improve a lower-bound for nonconvex problem by successively solving relaxed (convex) problem with α calculated at z_0 equal to SINR from previous iteration.

Dual problem

$$\max_{\lambda \in \mathbb{R}_+^L} g(\lambda) = \sum_{n=1}^N g_n(\lambda),$$

$$g_n(\lambda) = \inf_{\tilde{\mathbf{P}}^n \leq \log(\mathbf{S}_{max}^n)} -\phi_n(\tilde{\mathbf{P}}^n) + \left\langle \lambda, e^{\tilde{\mathbf{P}}^n} - \frac{\mathbf{P}_{max}}{N} \right\rangle,$$

where λ – Lagrange multipliers, or equivalently

$$\begin{aligned} \min_{\lambda \in \mathbb{R}^L, \mathbf{z} \in \mathbb{R}_+^{NL}} \sum_{n=1}^N -g_n(\mathbf{z}_n) \\ \text{s.t. } \lambda - \mathbf{z}_n = 0, \quad n = 1, \dots, N, \end{aligned}$$

\mathbf{z} – artificial variables.

Augmented Lagrangian for above problem:

$$L_{\rho}(\boldsymbol{\lambda}, \mathbf{z}, \mathbf{y}) = \sum_{n=1}^N \left[-g_n(\mathbf{z}_n) + \langle \mathbf{y}_n, \boldsymbol{\lambda} - \mathbf{z}_n \rangle + \frac{\rho}{2} \|\boldsymbol{\lambda} - \mathbf{z}_n\|^2 \right],$$

\mathbf{y} – Lagrange multipliers; $\rho > 0$ – penalty parameter.

ADMM applied to dual problem:

$$\boldsymbol{\lambda}^{(k+1)} = \arg \min_{\boldsymbol{\lambda} \in \mathbb{R}^L} \left\langle \sum_{n=1}^N \mathbf{y}_n^{(k)}, \boldsymbol{\lambda} \right\rangle + \frac{\rho}{2} \sum_{n=1}^N \left\| \boldsymbol{\lambda} - \mathbf{z}_n^{(k)} \right\|^2,$$

$$\mathbf{z}_n^{(k+1)} = \arg \max_{\mathbf{z}_n \geq 0} g_n(\mathbf{z}_n) + \langle \mathbf{y}_n^{(k)}, \mathbf{z}_n \rangle - \frac{\rho}{2} \left\| \boldsymbol{\lambda}^{(k+1)} - \mathbf{z}_n \right\|^2,$$

$$\mathbf{y}_n^{(k+1)} = \mathbf{y}_n^{(k)} + \rho \left(\boldsymbol{\lambda}^{(k+1)} - \mathbf{z}_n^{(k+1)} \right), \quad n = 1, \dots, N.$$

For $\boldsymbol{\lambda}$ and \mathbf{z}_n we have a solution in an explicit form.

Final algorithm:

Choose $\rho > 0$, $\mathbf{z}_n^{(0)}$, $\mathbf{y}_n^{(0)}$, $n = 1, \dots, N$; then repeat

$$\textcircled{1} \quad \boldsymbol{\lambda}^{(k+1)} = \frac{1}{N} \sum_{n=1}^N \left(\mathbf{z}_n^{(k)} - \frac{1}{\rho} \mathbf{y}_n^{(k)} \right)$$

$\textcircled{2}$ For each $n = 1, \dots, N$ solve **in parallel** N convex problems

$$\begin{aligned} (\tilde{\mathbf{P}}^n)^{(k+1)} = & \arg \min_{\tilde{\mathbf{P}}^n \leq \log(\mathbf{S}_{max}^n)} -\phi_n(\tilde{\mathbf{P}}^n) \\ & + \frac{\rho}{2} \sum_{l=1}^L \left(\left[\lambda_l^{(k+1)} + \frac{1}{\rho} \left(y_{ln}^{(k)} + e^{\tilde{P}_l^n} - \frac{P_{l,max}}{N} \right) \right]^+ \right)^2 \end{aligned}$$

$$\mathbf{z}_{ln}^{(k+1)} = \left[\lambda_l^{(k+1)} + \frac{1}{\rho} \left(y_{ln}^{(k)} + e^{(\tilde{P}_l^n)^{(k+1)}} - \frac{P_{l,max}}{N} \right) \right]^+,$$

$$\textcircled{3} \quad \mathbf{y}_n^{(k+1)} = \mathbf{y}_n^{(k)} + \rho \left(\boldsymbol{\lambda}^{(k+1)} - \mathbf{z}_n^{(k+1)} \right), \quad n = 1, \dots, N,$$

where we use the notation $x^+ = \max(0, x)$.

Numerical examples. Scenario:

Network with wrap-around topology

Number of cells: $L = 37$

Inter cell distance: 2500 m

System frequency: 2110 MHz

System bandwidth: 10 MHz

Number of resource blocks: $N = 50$

Maximum cell transmit power $P_{l,max} = 40$ W

Users: 20 users at each cell distributed close to the cell-edge at the distance 0.6..0.9 of cell radius and moving with the speed of 3 km/h

Standard deviation for the log-normal fading: 8 dB

Log-normal correlation downlink: 0.5

Log-normal fading correlation distance: 100 m

Channel model: ITU PedA

Antenna Techniques: SISO

Thermal Noise: $5.7e-15$ W

Traffic Model: Full-buffer

Results

ADMM was compared with subgradient (SG) and ellipsoid (EL) methods which are used for solving dual problems (NCVX and SCALE)

[NCVX]:

SG	OFV	6614.9
	NII	228

[SCALE]:

NOI		1	2	3	4	5	6	7	8	9	10
SG	OFV	6619.9	6622.5	6623.1	6623.1	6623.2	6622.1	6622.8	6623.2	6622.1	6622.9
	NII	68	30	193	9	20	27	24	5	42	34
ADMM	OFV	6621	6623.1	6623.2	6623.2	6623.2	6623.2	6623.2			
	NII	2	1	1	1	1	1	1			
EL	OFV	6619.4	6621.5	6621.7	6621.7	6621.7	6621.7	6621.7			
	NII	160	164	170	170	169	170	170			

NOI – number of outer iterations (α -update)

NII – number of inner iterations (Lagrange multipliers update)

OFV – objective function value (weighted sum rate)

Conclusions

- Developed method based on SCALE+ADMM approach for solving nonconvex weighted sum rate maximization problem
- Numerical simulations demonstrate the performance (less number of Lagrange multipliers updates) of proposed method compared with the existing ones: NCVX+SG (W. Yu et al) and SCALE+EL (L. Venturino et al)

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Thank you!

Stopping criteria (Boyd et al):

$$\left\| \mathbf{r}_{pri}^{(k)} \right\|_2 \leq \epsilon_{pri}$$

and

$$\left\| \mathbf{r}_{dual}^{(k)} \right\|_2 \leq \epsilon_{dual}$$

where the primal and dual residuals

$$\mathbf{r}_{pri}^{(k)} = \left[\boldsymbol{\lambda}^{(k)} - \mathbf{z}_n^{(k)} \right]_1^N$$

$$\mathbf{r}_{dual}^{(k)} = -\rho \left(\mathbf{z}^{(k)} - \mathbf{z}^{(k-1)} \right)$$