ENERGY-EFFICIENT JOINT TRANSMIT BEAMFORMING AND SUBARRAY SELECTION WITH NON-LINEAR POWER AMPLIFIER EFFICIENCY

Oskari Tervo, Le-Nam Tran, and Markku Juntti

Centre for Wireless Communications, University of Oulu, Oulu, Finland

UNIVERSITY OF OULU

CWC CENTRE FOR WIRELESS COMMUNICATIONS University of Oulu

IEEE Global Conference on Signal and Information Processing (GlobalSIP)

Dec 7-9, 2016 – Washington, USA

Abstract

Multi-user single-cell MISO downlink transmission

Key Idea:

- Improve energy efficiency with joint beamforming and subarray selection
  - Antenna array divided into subarrays, each connected to a common RF chain → Less RF chains
  - Output power dependent power amplifier efficiency model

Optimization Problem:

- Energy efficiency maximization

Proposed solution:

- Continuous relaxation and successive convex approximation with additional penalty term in the objective function

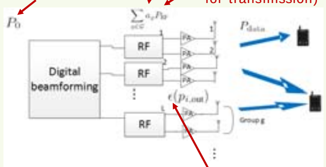
System Model

- Power consumption model:

Binary subarray selection variable

Fixed power consumption of all the other parts

Power consumption per active RF chain (i.e., if subarray g is selected for transmission)

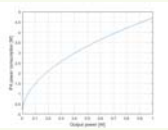


Each PA efficiency depends on its output power

- **PA power consumption (class B) [10]:**

Constant (>1)

$$p_{i,\text{data}}(p_{i,\text{out}}) \triangleq c\sqrt{P_{\max}}\sqrt{p_{i,\text{out}}}$$



Efficiency maximized at maximum output power

- **Total power consumption:**

$$u_i = c_i\sqrt{P_{\max}}$$

Power consumption scales with square root of output power of PA i

$$P_{\text{tot}} = \sum_{i\in\mathcal{N}} u_i \|\hat{\mathbf{w}}_i\|_2 + \sum_{g\in\mathcal{G}} a_g P_{\text{RF}} + P_0$$

$$\hat{\mathbf{w}}_i \triangleq [[\mathbf{w}_1]_i, [\mathbf{w}_2]_i, \cdots, [\mathbf{w}_K]_i]^T$$

- **Antenna elements are divided into G groups (subarrays)**
- **Each antenna group is connected to a single RF chain**
- **Each antenna has its own power amplifier**
- **The number of RF chains can be smaller than the number of subarrays (we can perform subarray selection by using an RF switch)**

Problem Formulation

$$\gamma_k(\mathbf{w}) \triangleq \frac{|\mathbf{h}_k\mathbf{w}_k|^2}{N_0 + \sum_{j\in\mathcal{K}, j\neq k}|\mathbf{h}_k\mathbf{w}_j|^2}$$

$$\max_{\mathbf{w},\mathbf{v},\mathbf{a}} \frac{\sum_{k\in\mathcal{K}} R_k(\mathbf{w})}{\sum_{i\in\mathcal{N}} u_i\|\hat{\mathbf{w}}_i\|_2 + \sum_{g\in\mathcal{G}} a_g P_{\text{RF}} + P_0}$$

s. t.

$\gamma_k \geq \bar{\gamma}_k, \forall k \in \mathcal{K}$ (1) SINR constraints

$\|\bar{\mathbf{w}}_g\|_2^2 \leq a_g v_g, \forall g \in \mathcal{G}$ (2) Guarantees $a_g = 0 \Rightarrow \bar{\mathbf{w}}_g = 0$

$v_g \leq P_g, \forall g \in \mathcal{G}$ (3) Subarray specific power constraint

$\sum_{g\in\mathcal{G}} a_g \leq L$ (4) Maximum number of RF chains

$a_g \in \{0,1\}, \forall g \in \mathcal{G}$ (5) Binary subarray selection variables

Equivalent Transformation

Variables: $t, z, \mathbf{w}, \mathbf{a}, \mathbf{v}$

$$\max \quad t$$

s. t.

$\sum_{k\in\mathcal{K}} \log(1+\gamma_k) \geq \sqrt{tz}$ (6) Nonconvex

$\sqrt{z} \geq \sum_{i\in\mathcal{N}} u_i\|\hat{\mathbf{w}}_i\|_2 + \sum_{g\in\mathcal{N}_g} a_g P_{\text{RF}} + P_0$ (7) Convex

$0 \leq a_g \leq 1, \forall g \in \mathcal{G}$ (8) Convex continuous relaxation

$\frac{1}{\sqrt{\bar{\gamma}_k}}\mathbf{h}_k\mathbf{w}_k \geq \left(N_0 + \sum_{j\in\mathcal{K}, j\neq k}|\mathbf{h}_k\mathbf{w}_j|^2\right)^{\frac{1}{2}}, \text{Im}(\mathbf{h}_k\mathbf{w}_k) = 0$ (9) Equivalent convex form of the SINR constraint

(2)-(4) Convex

Penalized Formulation

$$\max \quad t - \rho\sum_{g\in\mathcal{G}} v_g$$

Penalty term which promotes sparsity of $\mathbf{a}$

s. t.

$\mathbf{h}_k\mathbf{w}_k \geq \sqrt{(\vartheta_k - 1)\beta_k}, \forall k \in \mathcal{K}$ (10) Linear >= concave

$\sum_{k\in\mathcal{K}} \alpha_k \geq \sqrt{tz}$ (11)

$\vartheta_k \geq e^{\alpha_k}, \forall k \in \mathcal{K}$ (12)

$\beta_k \geq N_0 + \sum_{j\in\mathcal{K}, j\neq k}|\mathbf{h}_k\mathbf{w}_j|^2, \forall k \in \mathcal{K}$ (13)

Equivalent transformations of (6)

(2)-(4), (7)-(9)

Variables: $t, z, \mathbf{w}, \mathbf{a}, \mathbf{v}, \boldsymbol{\vartheta}, \boldsymbol{\alpha}, \boldsymbol{\beta}$

Successive Convex Approximation

- Solve a convex problem iteratively

$$\max \quad t - \rho\sum_{g\in\mathcal{G}} v_g$$

s. t.

$\mathbf{h}_k\mathbf{w}_k \geq LA^{(n)}(\vartheta_k, \beta_k), \forall k \in \mathcal{K}$

$\sum_{k\in\mathcal{K}} \alpha_k \geq LA^{(n)}(t, z)$

Linear upper approximations of RHS of (10) and (11)

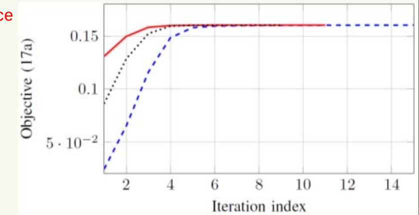
(2)-(4), (7)-(9), (12)-(13)

Recover the Binary Solution

- Many of the binary variables converge to zero → round all the non-zero variables to one
- Run SCA again for the chosen antenna set to find the beamformers

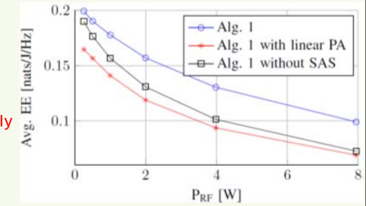
Convergence example

- Fast convergence for the relaxed problem with different initial points

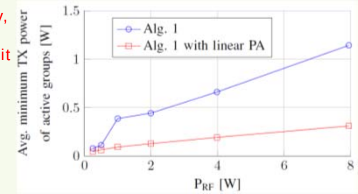


Comparison to Other Methods

- EE gains over the method with linear PA and a method without subarray selection
- Linear PA model greatly over-estimates efficiency → Results can be really bad



- With fixed PA efficiency, we tend to transmit with very small transmit power → more active subarrays
- With output power dependent model, use less subarrays with higher transmit power



- Note: 'Linear PA' means that the efficiency is assumed to be maximum for all the output power values (i.e., it is equal to non-linear efficiency with maximum power)

Conclusion

- Energy-efficient joint beamforming and subarray selection with output-power dependent PA efficiency

[10] X. Shi, W. Xu, X. Zhou, and J. Lin, "Energy efficiency optimization in OFDM-based cognitive radio systems: Impact of power amplifiers," in *IEEE 81st Veh. Tech. Conf.*, May 2015, pp. 1–5.