



Learning-Based Antenna Selection for Multicasting

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Abstract

- Multicast transmit beamforming is an efficient technique for increasing the capacity of multi-antenna systems.
- Activating a subset of the available transmit antennas → save hardware and energy resources
- However, multicast with antenna selection is NP-hard
- Prior art uses semi-definite relaxation techniques and first-order SCA to obtain approximate solutions → still far from implementation in real time.
- Neural network-based approach will be used to obtain a real time antenna selection solutions
- Numerical results show that the efficacy of the proposed machine learning approach relative to the prior state-of-art

Background

Multicast beamforming: Two basic design problems

$$\max_{\mathbf{w} \in \mathbb{C}^n} \min_m \mathbf{w}^H \mathbf{A}_m \mathbf{w}$$

s. to $\|\mathbf{w}\|^2 \leq P$

$$\min_{\mathbf{w} \in \mathbb{C}^n} \|\mathbf{w}\|^2$$

s. to $|\mathbf{w}^H \mathbf{h}_m| \geq 1 \forall m$

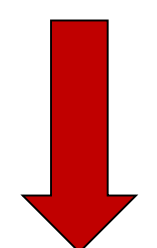
- Non-convex and Np-hard problems
- Semidefinite relaxation(SDR)-based approaches have been shown effective in identifying near-optimal solutions for both problems.[Sidiropoulos'06]
- First order-based methods have been used to obtain approximate solutions to the problem [Konar'17]

Joint multicast beamforming and antenna selection

The goal is to jointly select the "best" subset of antennas and the corresponding beam-forming vectors that can maximize the minimum received SNR among the users

$$\max_{\mathbf{w} \in \mathbb{C}^n} \min_m \mathbf{w}^H \mathbf{A}_m \mathbf{w}$$

s. to $\|\mathbf{w}\|^2 \leq P, \|\mathbf{w}\|_0 \leq K$



$$\max_{\mathbf{w} \in \mathbb{C}^n} \min_m \mathbf{w}^H \mathbf{A}_m \mathbf{w} - \lambda \|\mathbf{w}\|_1$$

s. to $\|\mathbf{w}\|^2 \leq P$

- More difficult problem.. It needs exhaustive search to get the optimal set of antennas.
- SDR technique is used to get an approximate solution. [Mehanna'13]
- Saddle-Point Mirror-Prox (SP-MP) algorithm is used to obtain sub-optimal solution [Salah'18]

Motivation

Binary search: Regardless of the high-quality solution obtained by both SDR or the first order SPMP, both of them requires binary search over the value of λ
→ Binary search requires much time

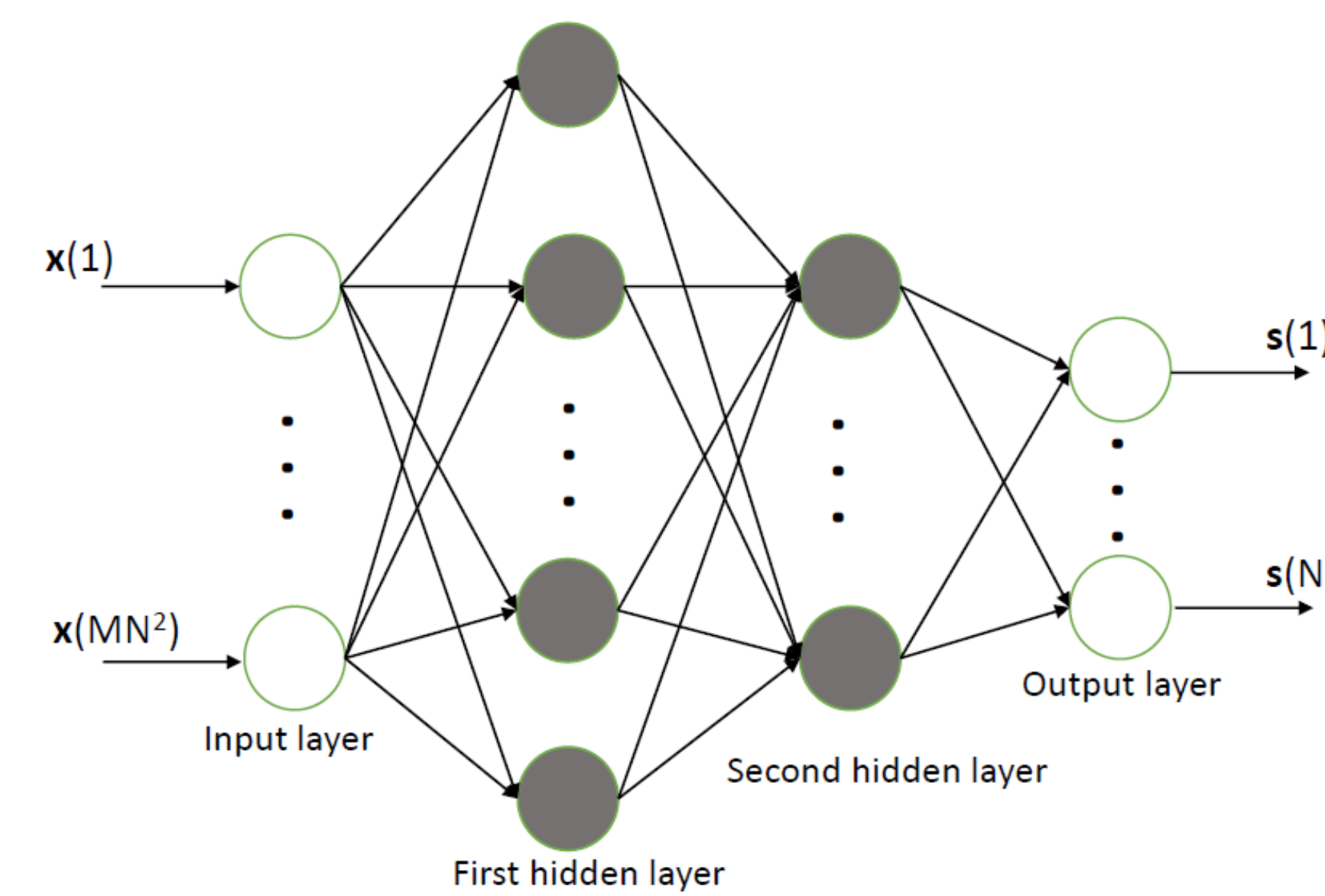
Q: How to avoid this binary search procedure?

A: Train deep neural network to map the channel inputs to antenna selection solutions.

Q: Why SP-MP instead of SDR?

A: SP-MP proved to provide high-quality low-complexity solution than that of SDP

Proposed Approach



Two stage approach:

- Stage 1: Training a deep neural network to map the second order information of the channel to binary vector that represents the set of active antennas that was selected using the SP-MP algorithm
- Stage 2: Solve a reduced size problem using the SP_MP algorithm to get the corresponding beam-forming vector.

Training the neural network:

- The **second order information** is used to train the network $\mathbf{A}_m = \mathbf{h}_m \mathbf{h}_m^H, \forall m \in \{1, \dots, M\}$
→ saves network resources and internal conversions
- But.. \mathbf{A}_m is a hermitian matrix
→ only upper triangular part can be used in training

How can we obtain the training data set?

- The SP-MP algorithm is used to generate the training data set.
→ very fast convergence rate and high quality solution
- The i -th training contains the tuple $(\mathbf{x}_i, \mathbf{s}_i)$, where the output is a binary vector that corresponds to the set of active antenna for a given input.

Proposed Approach (cont.)

Neural network setting

- The neural network has two hidden layers
- The input size is MN^2 while the output size is N
- The number of nodes in the first layer is double the input size while in the second one is the same size of the input.
- The activation function of both layers is Log-Sigmoid.

Testing stage steps

- Channel realizations are generated following the same distribution as the training stage
- The upper triangular parts of the second order information matrices are fed to the neural network
- The largest K out of the N outputs are considered to be the set of active antennas
- The SP-MP algorithm is utilized to solve a reduced size problem with the set of active antennas to get the corresponding beam-forming vector that attains the max-min SNR

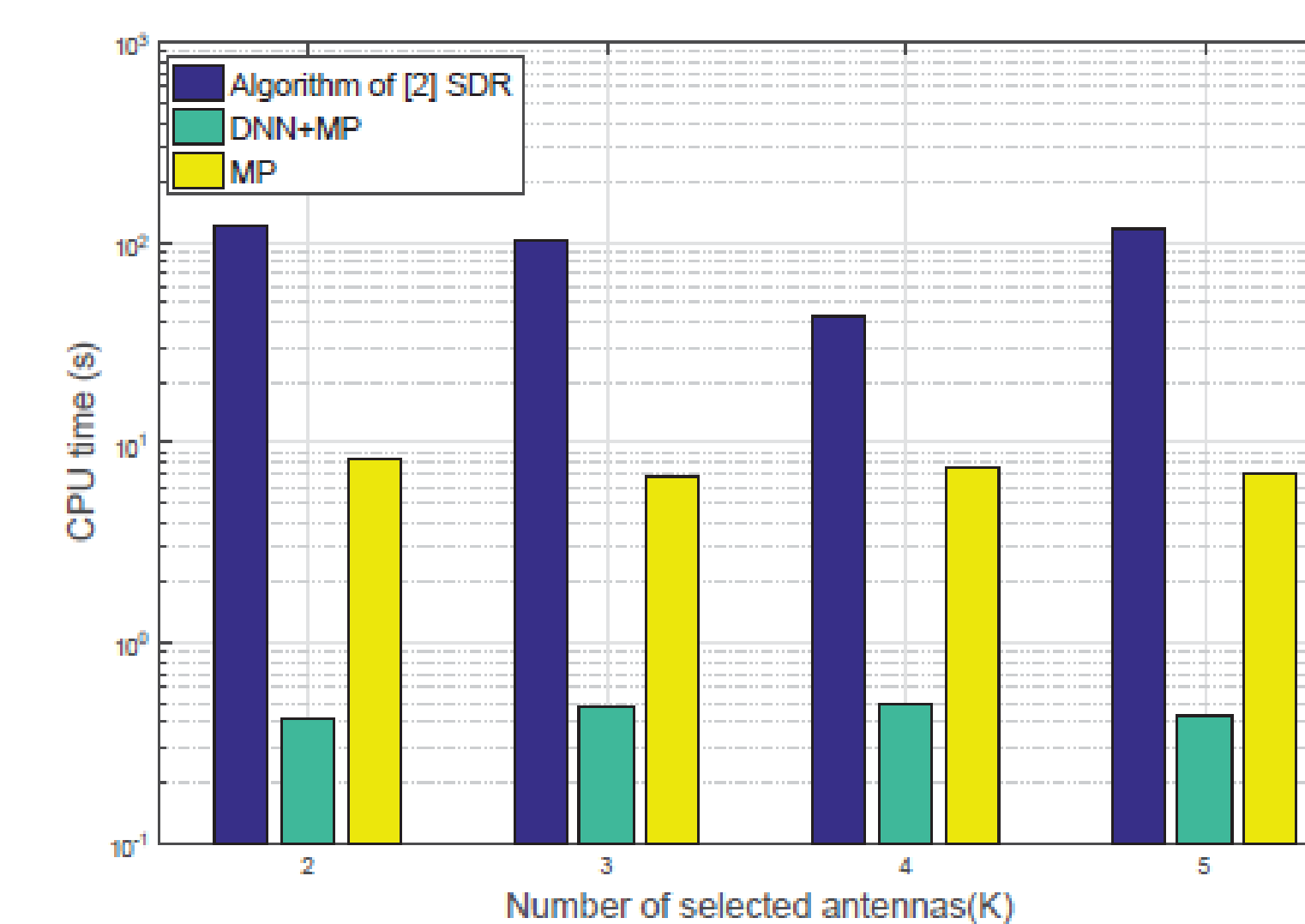
Experiments

Simulation parameters:

- We consider a scenario with $N = 6$ and $M = 10$
- The downlink channels are modeled as random vector drawn from normal distribution
- The noise variance was set to 1
- The total transmission power was set to 10

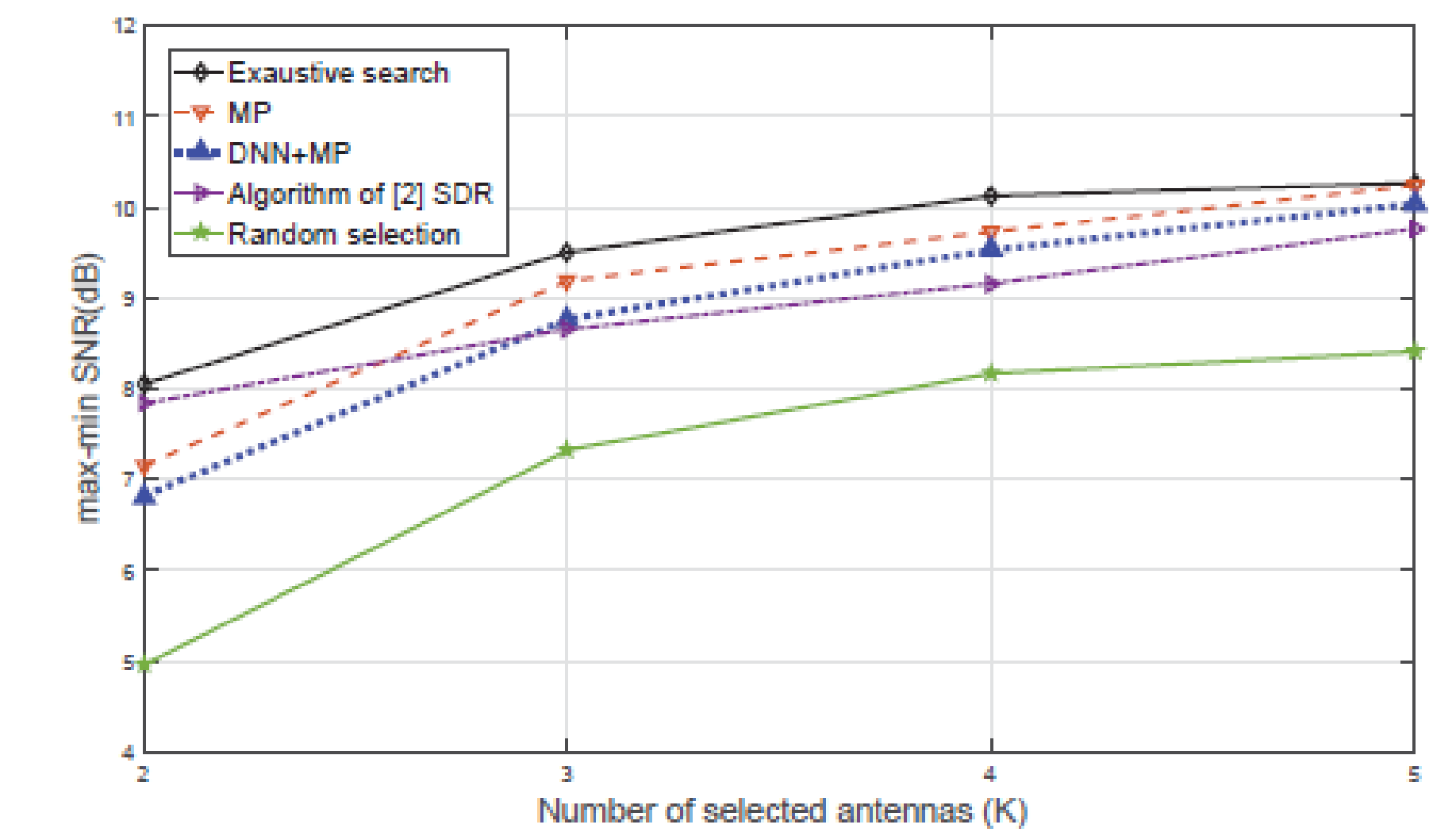
Neural network parameters:

- In the training stage, 30000 channel realizations were used
- 3% of them used for validation
- The learning rate was set to 0.01



CPU time vs K, N=6

Experiments (cont.)



max-min SNR vs K, N = 6

Baseline Algorithms:

- Exhaustive search
→ optimal solution but very expensive
→ used as upper bound
- Random selection
→ very cheap but the worst performance
→ used as lower bound
- Semi-definite relaxation
→ High quality solution but expensive when N increases
- Mirror prox SCA
→ High quality and low complexity solution
→ The best one across the benchmarked algorithms
→ still can not be implemented in real-time due to the binary search procedure

Results and Conclusion

- Proposed a two-stage approach that can handle the joint antenna selection and multicast beamforming problem.
- Key idea: Leveraging the computational efficiency of the DNN to solve the problem in real-time.
- Simulations demonstrated that the proposed DNN with the MP algorithm provides substantial computational relative to traditional methods