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Joint Transmit and Receive Antenna Selection Using a Probabilistic Distribution Learning Algorithm in MIMO Systems

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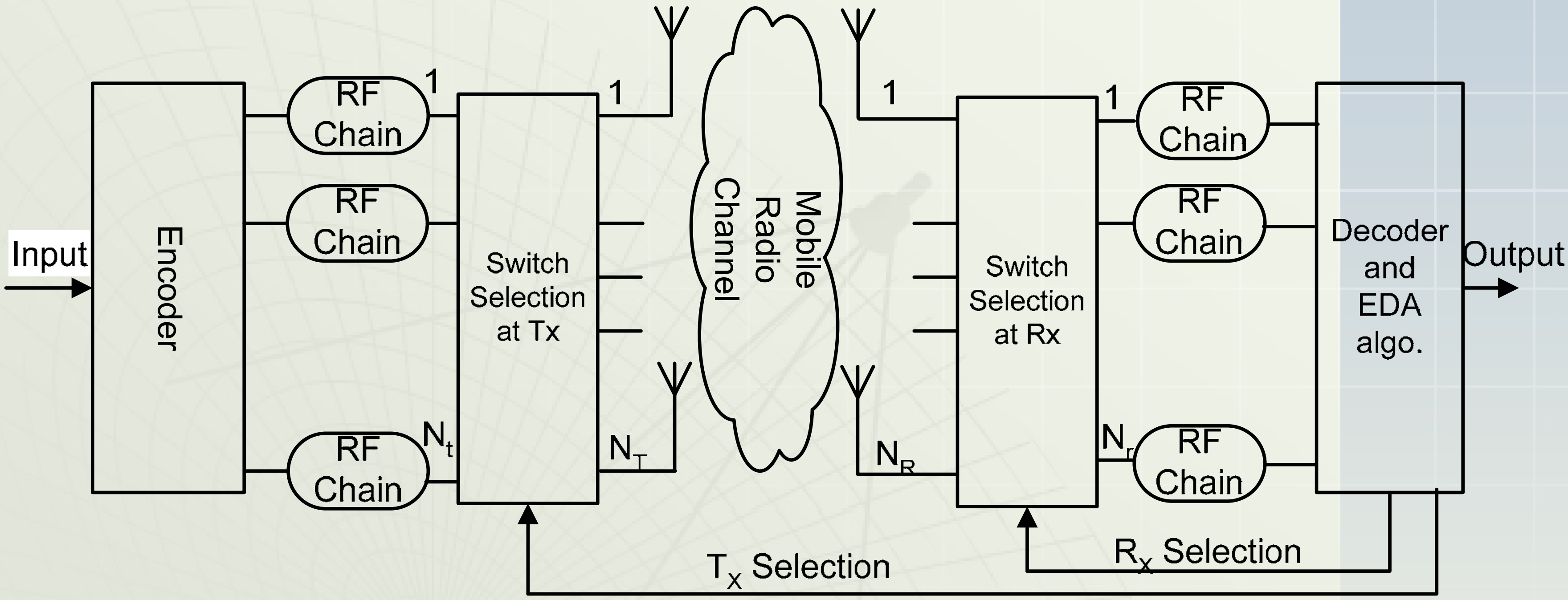
Outline

- Motivation and Problem Formulation
- Estimation of Distribution Algorithm (EDA)
- Improved EDA
- Performance Comparison
- Conclusion

MIMO System



•Capacity of a MIMO system increases with the number of antennas

•Larger number of antennas results in a high hardware cost due to the large number of RF chains

Motivation

Hardware cost can be significantly reduced by selecting a subset of antennas from the set of physically available antennas and using the signals from the selected antennas only, without sacrificing the advantage of multi antenna diversity.

We need to Choose N_t transmit antennas from N_T transmit antennas and similarly N_r receive antennas from N_R receive antennas

Motivation

We denote by Φ the collection of all possible joint transmit and receive antenna selections. Then, the number of possible ways of selecting antennas is

$$|\Phi| = \binom{N_R}{N_r} \times \binom{N_T}{N_t}$$

The computational complexity of finding an optimal Joint Transmit and Receive Antenna selection by exhaustive search grows exponentially with the number of transmit and receive antennas.

Joint Antenna Selection Problem

We denote by ϕ in Φ a selection of transmit and receive antennas.

We denote by $H^{\phi} \in \mathbb{C}^{N_r \times N_t}$ the channels formed between selected N_t transmit antennas and N_r receive antennas. The channel capacity associated with selected transmit and receive antennas is

$$C(H^{\phi}) = \log_2 \det\left(I_{N_r} + \frac{\rho}{N_t}(H^{\phi})(H^{\phi})^H \right)$$

where ρ is the average SNR per channel use.

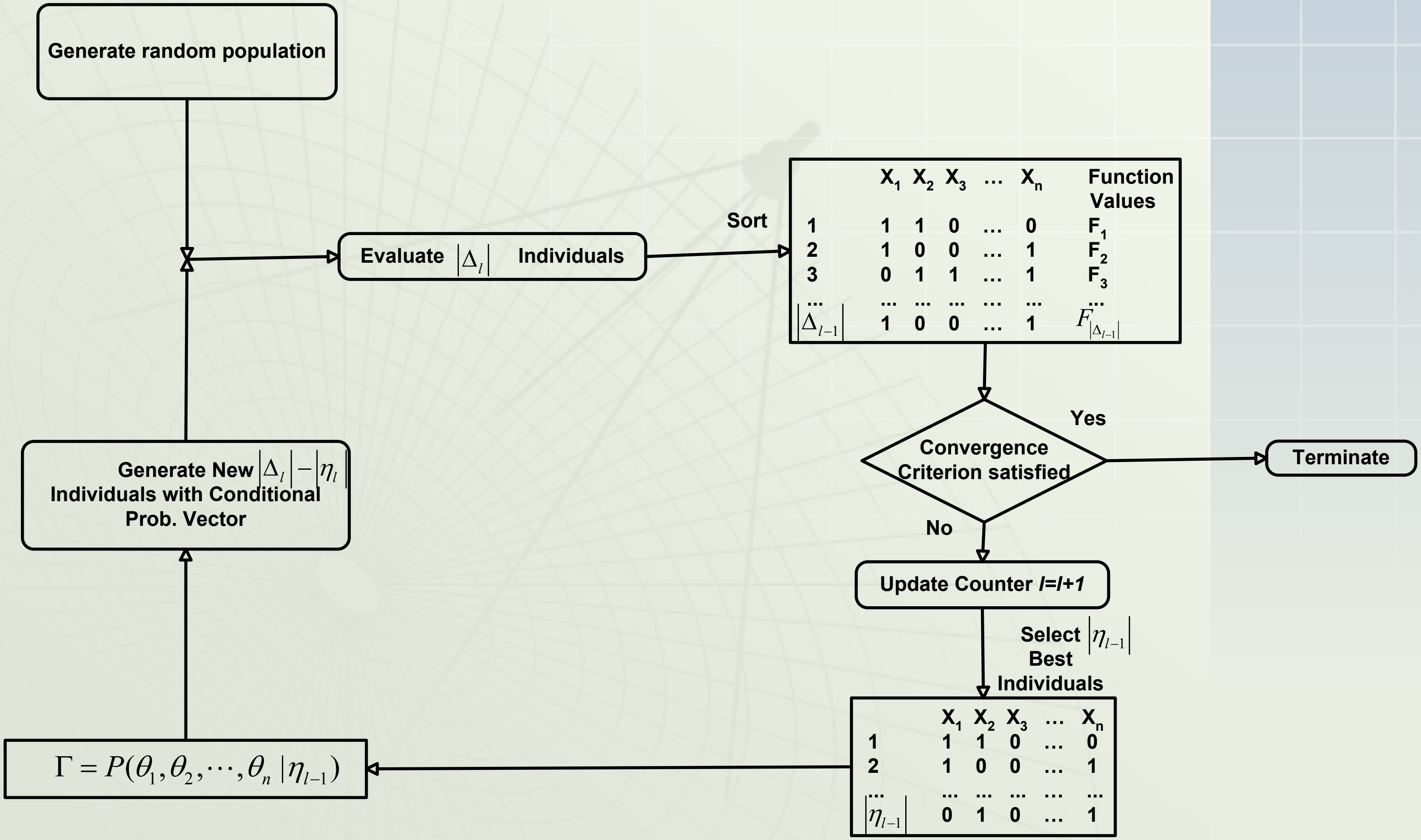
Joint Antenna Selection Problem

We can model joint transmit and receive antenna selection problem as a combinatorial optimization problem

$$\max_{\phi \in \Phi} C(H^{\phi}) \text{ or}$$

$$\max_{\phi \in \Phi} \log_2 \det\left(I_{N_r} + \frac{\rho}{N_t} (H^{\phi})(H^{\phi})^H \right)$$

Conventional EDA

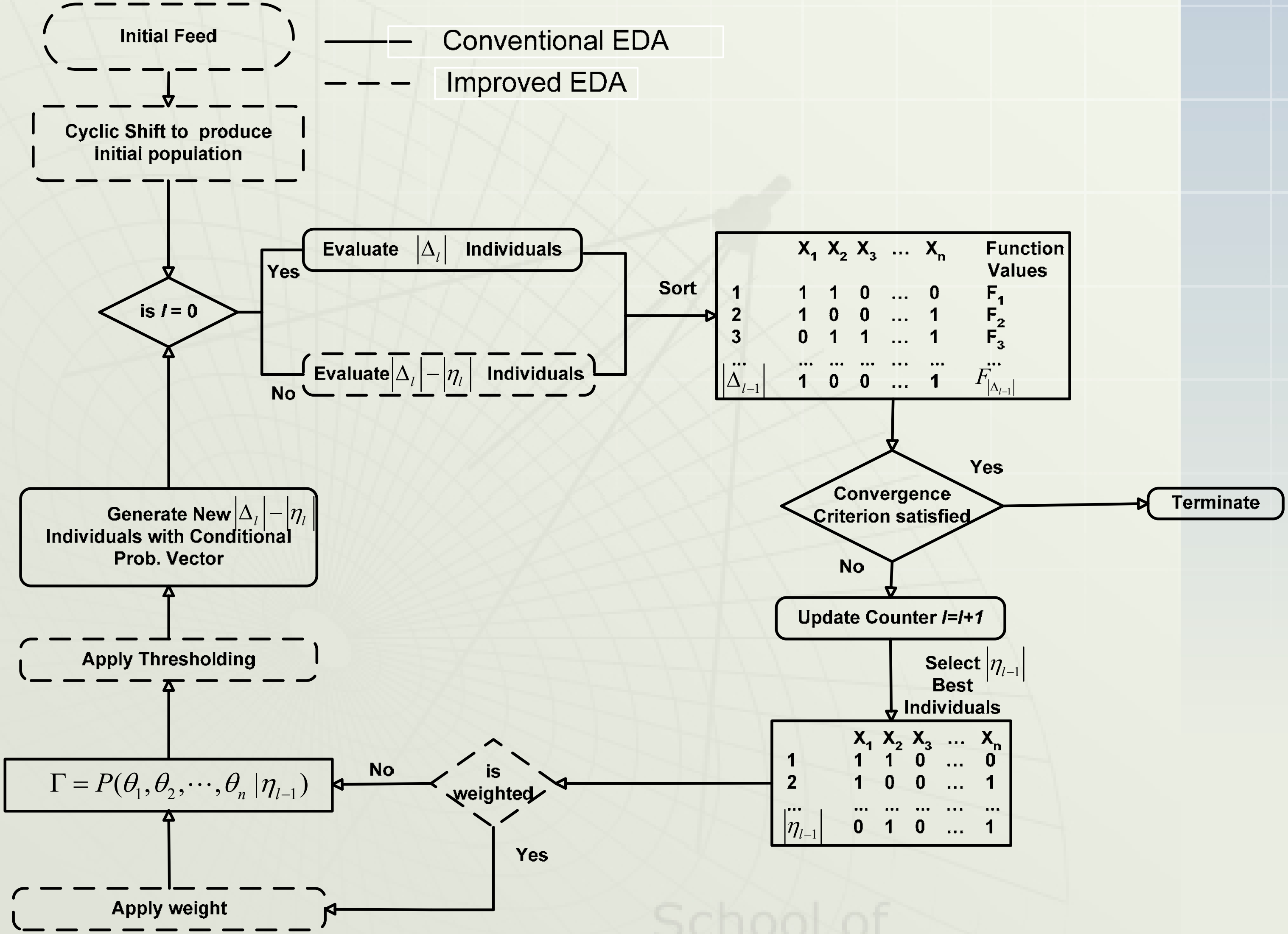


EDA

EDA can be characterized by parameters and Notations

1. I_s is the space of all potential solutions
2. $F(\,)$ denotes a fitness function.
3. Δ_l is the set of individuals (population) at the l_{th} iteration.
4. η_l is the set of best candidate solutions selected from set Δ_l at the l_{th} iteration.
5. We denote $\beta_l \equiv \Delta_l - \eta_l \equiv \Delta_l \cap \eta_{c\,l}$ .where $\eta_{c\,l}$ is the complement of η_l.
6. p_s is the selection probability. The EDA algorithm selects $p_s|\Delta_l|$ individuals from set Δ_l to make up set η_l.
7. We denote by Γ the distribution estimated from η_l (the set of selected candidate solutions) at each iteration
8. I_{Ter} are the maximum number of iteration

Modified EDA



Generating the initial population

Transmit selection Initial Feed = [1 1 1 0 0 0 0]

Receive selection Initial Feed = [1 0 0 0 0 1 1]

Cyclic shift on TX initial feed

	TX_1	TX_2	TX_3	TX_4	TX_5	TX_6	TX_7
1	1	1	1	0	0	0	0
2	0	1	1	1	0	0	0
3	0	0	1	1	1	0	0
4	0	0	0	1	1	1	0
5	0	0	0	0	1	1	1
6	1	0	0	0	0	1	1
7	1	1	0	0	0	0	1

Cyclic shift on RX initial feed

	RX_1	RX_2	RX_3	RX_4	RX_5	RX_6	RX_7
1	1	0	0	0	0	1	1
2	1	1	0	0	0	0	1
3	1	1	1	0	0	0	0
4	0	1	1	1	0	0	0
5	0	0	1	1	1	0	0
6	0	0	0	1	1	1	0
7	0	0	0	0	1	1	1

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}
1	1	1	1	0	0	0	0	1	0	0	0	0	1	1
2	0	1	1	1	0	0	0	1	1	0	0	0	0	1
3	0	0	1	1	1	0	0	1	1	1	0	0	0	0
4	0	0	0	1	1	1	0	0	1	1	1	0	0	0
5	0	0	0	0	1	1	1	0	0	1	1	1	0	0
6	1	0	0	0	0	1	1	0	0	0	1	1	1	0
7	1	1	0	0	0	0	1	0	0	0	0	1	1	1

Concatenation of population generated by TX and RX cyclic shift

Weighted EDA

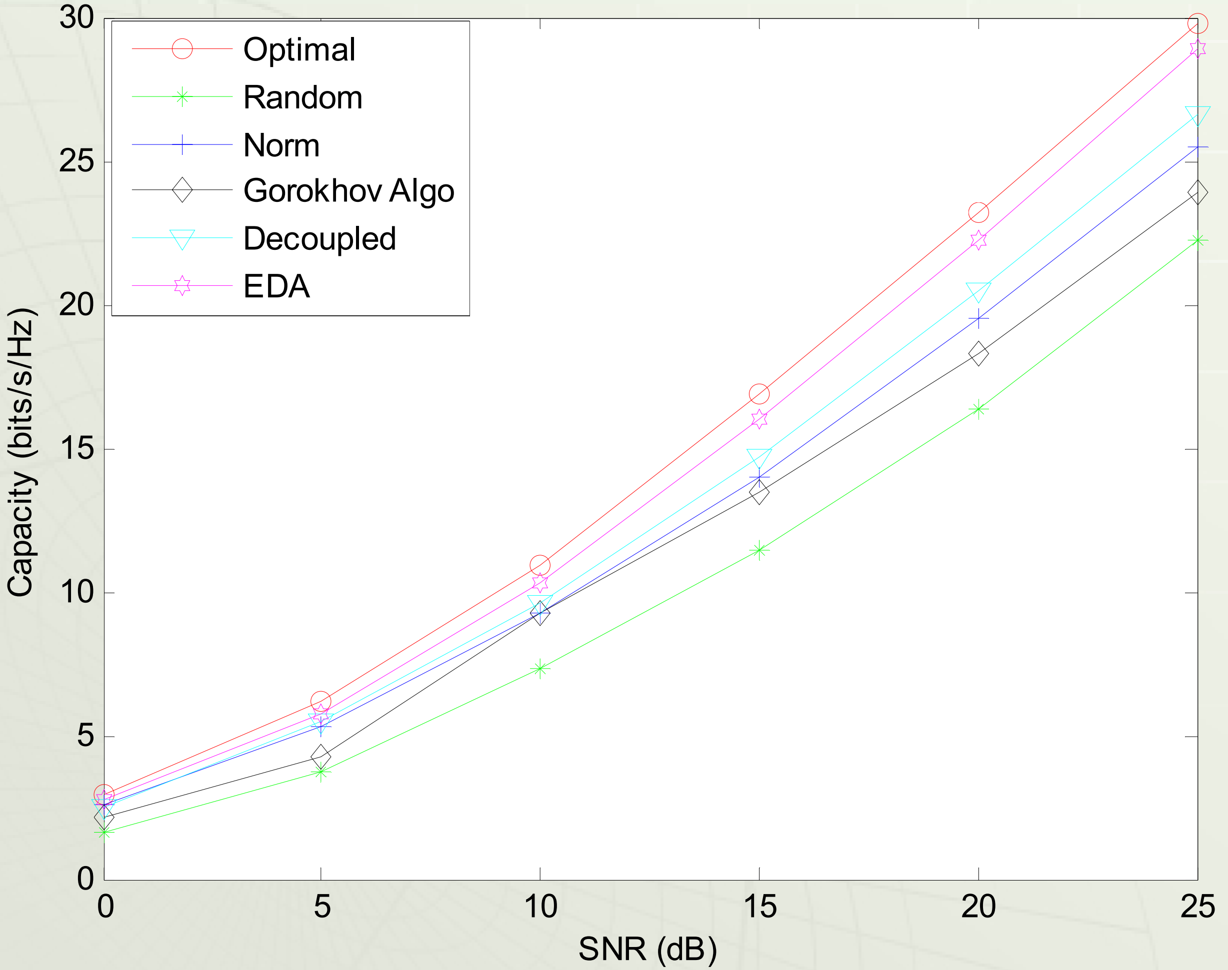
we propose an idea of adding some skew in estimating the probability distribution in EDA.

The skew can be added by giving more weights to the individuals in η_{l-1} that have better fitness in estimating the joint probability distribution

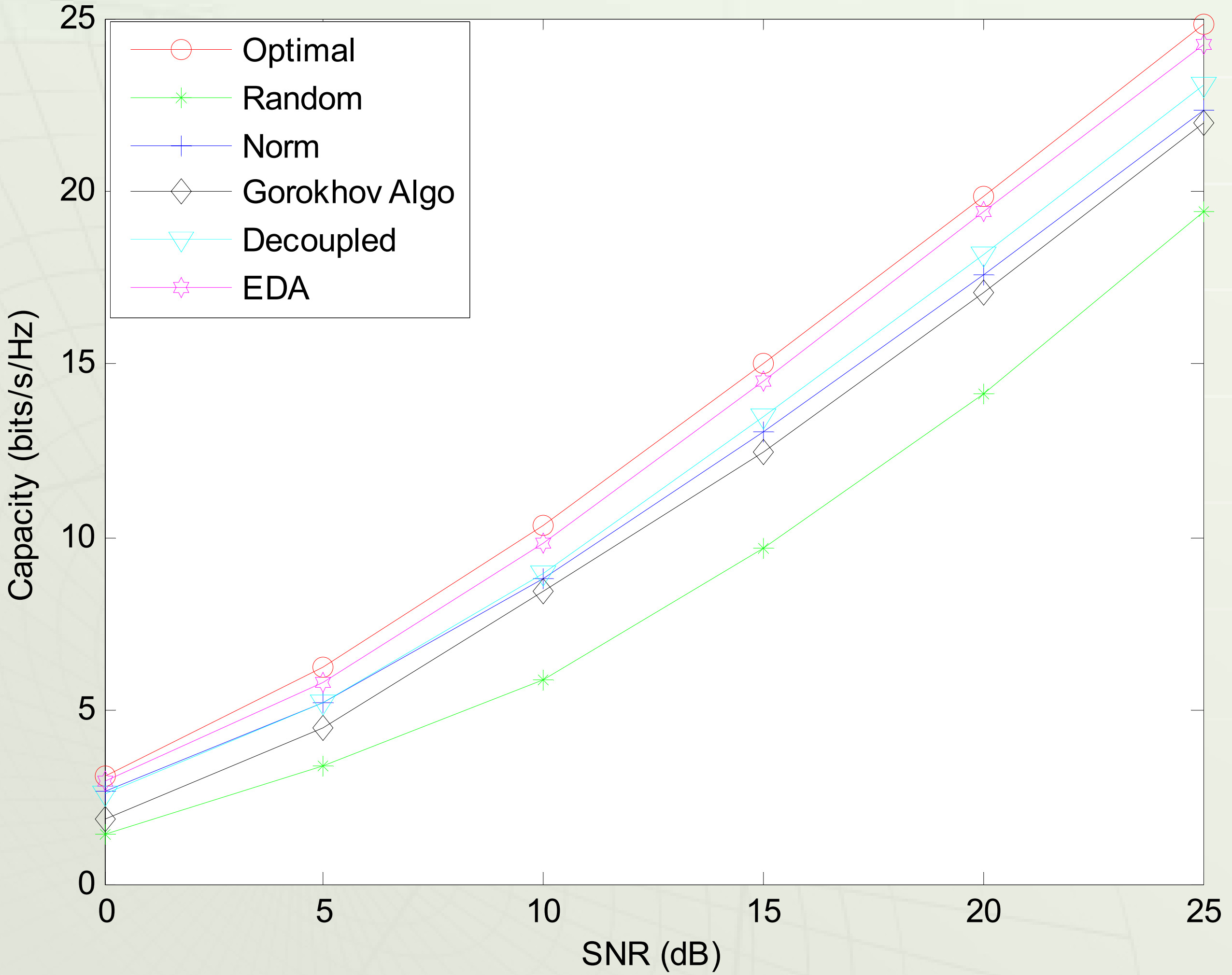
An example of Weight values is

$$\xi_j = \frac{\log\left(\left|\eta_l\right|\right) - \log\left(j\right)}{\sum_{i=1}^{\left|\eta_l\right|}\left[\log\left(\left|\eta_l\right|\right) - \log\left(i\right)\right]}, \quad j = 1, 2, \ldots, \left|\eta_l\right|$$

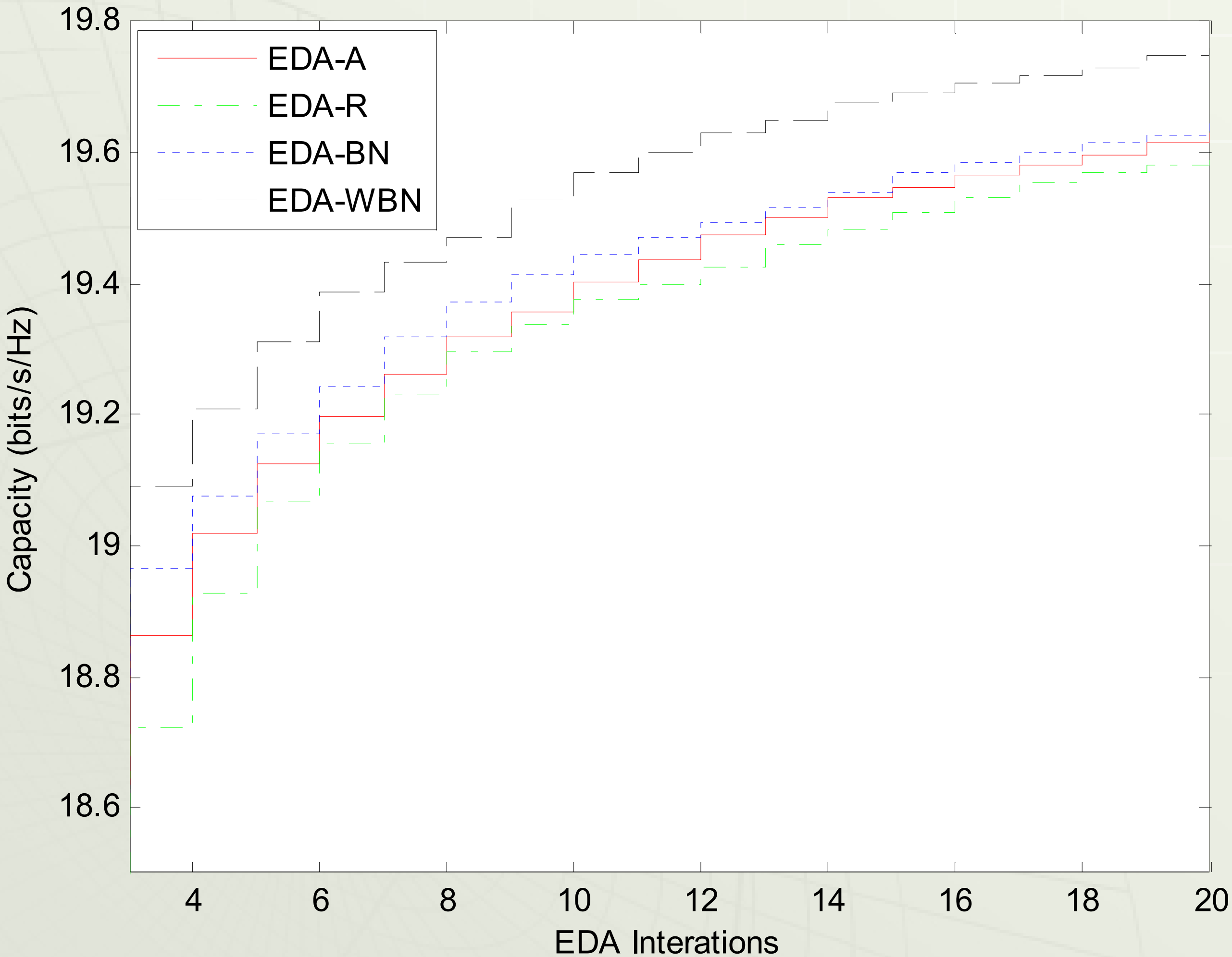
Simulation Results



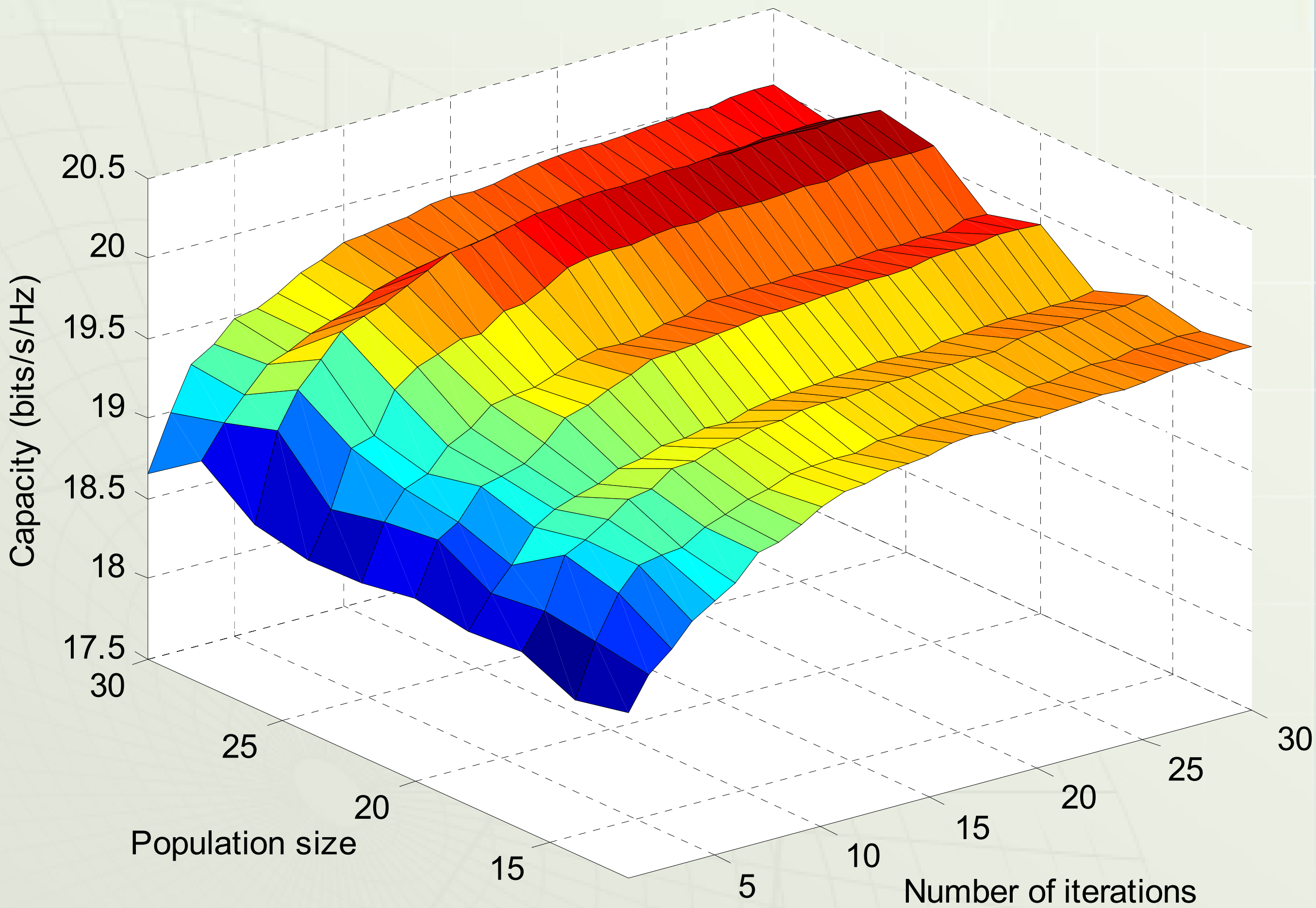
10% Outage capacity versus SNR. With NT=6, Nt=3, NR=30, Nr=2.



10% Outage capacity versus SNR. With *NT*=6, *Nt*=4, *NR*=18, *Nr*=3



10% Outage capacity versus EDA iterations



Tradeoff between population size and the number of iterations

The number of complex multiplications and additions

- ESA $$\left[\binom{N_R}{N_r}\times\binom{N_T}{N_t}\right]\times N_R^3$$
- Decoupled Algorithm $$\left[\binom{N_R}{N_r}+\binom{N_T}{N_t}\right]\times N_R^3$$
- Gorokhov $$N_R N_r N_t^3 + N_T N_t N_r^3$$
- EDA $$\left(|\Delta_l| I_{Ter}\right) N_R^3$$

The number of complex multiplications and additions

$\left[N_R, N_r, N_T, N_t, \lvert\Delta\rvert, I_{Ter}\right]$	ESA	Decoupled Algorithm	Gorokhov Algorithm	EDA
[30 , 2, 6, 3,30,20]	23200	1213	1794	1600
[16, 4, 6, 4, 16, 8]	582400	39147	5632	2730
[20, 4, 6, 4, 20,8]	1.5×10^6	103680	6656	3413
[20,8,10,6,20,8]	1.9×10^9	9.08×10^6	65280	11520

Conclusions

- Existing antenna selection schemes are computationally expensive.
- The performance of EDA algorithm is close to the optimal.
- EDA with Cyclic shifted initial population reduces the number of iterations to reach the optimal solution.
- The performance of weighted EDA is better than all variants of EDA.

Thank You