Base Station Cooperation for Mission Critical Communications

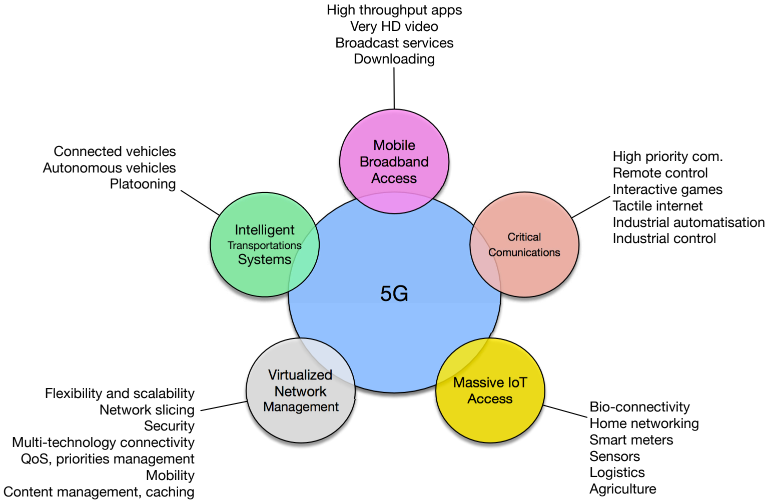
Marceau Coupechoux[1]

Joint work with Alaa Daher[2], Deepa Jagyasi[1], Philippe Godlewski[1]
with the help of the company ETELM (project EXTRANGE4G)
[1]Telecom Paris, Institut Polytechnique de Paris
[2]ETELM, France

IEEE Int. Conf. on Advanced Communication Technologies and Signal Processing (ACTS)

4 Dec. 2020

Future Wireless Networks Challenges



Mission Critical Communications

Source : ETELM

Mission Critical Communications

- MCC = All communications related to the safety and the security of the civil society. Public safety services, like police forces, firemen, rescue and ambulance services, or employees critical infrastructures, like energy and transportation suppliers
- MCC are conveyed by Professional Mobile Radio (PMR) networks
- One of the most important and indispensable services offered by mission-critical networks is the group communication
- MCC unique requirements : coverage, reliability and secure communications
- Group communication is based on Multimedia Broadcast/Multicast Service (MBMS) in 3GPP

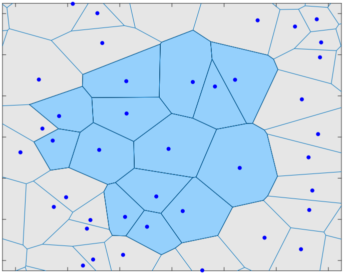
Mission Critical Communications

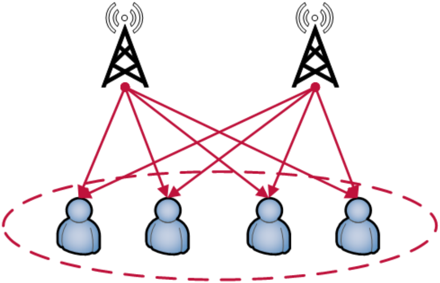
Outlines

Outline

Motivation

Multicast/Broadcast Single Frequency Network



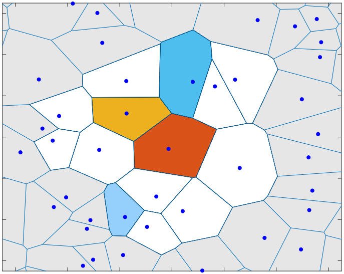


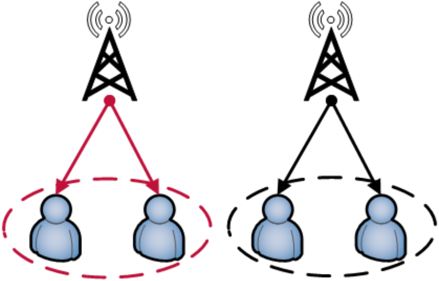
User SINRs are maximized

Radio resources can be wasted

Motivation

Single-Cell Point-To-Multipoint





Degraded user SINRs

Maximized network capacity

Motivation

SC-PTM	MBSFN
Degraded users SINRs	Users SINRs are maximized
Maximized network capacity	Radio resources can be wasted

Our objective : design a dynamic clustering algorithm to solve the reliability-capacity tradeoff in MCC

Clustering for cooperative transmissions

- State-of-the-art is mostly on unicast best effort traffic with the goal of maximizing user data rates under static traffic models
- Greedy algorithms based approaches have been widely used in network-centric clustering algorithms [PGH08, YKL16, DdV14, BBB14, Sch17]

$\Rightarrow$ Not optimal and requires adaptations for group communications

- Dynamic user centric clustering [LHYZ16, GZS14, LZG$^+$18, BJIX16, ZWZ$^+$17]

$\Rightarrow$ Focus on PHY data rate, dynamic traffic constraints ignored, only unicast, no reliability constraint

- MBMS literature [REH11, CCE$^+$15]

$\Rightarrow$ Do not address the reliability-capacity tradeoff

System Model

- Downlink of a cellular network
- A set $V = \{1, ..., n\}$ of n cells forming an MBSFN synchronization area
- A cluster is a subset $S \subseteq V$ serving a group $\mathcal{U}$ of users using multi-point transmissions
- Signal to Interference plus Noise Ratio (SINR) at user $u \in \mathcal{U}$:

$$\gamma_u(S) = \frac{\sum_{b \in S} \xi_{ub} g_{ub} P_T}{\sum_{b \in S} (1 - \xi_{ub}) g_{ub} P_T + \sum_{b \notin S} P_T g_{ub} + N_{th}}, \tag{1}$$

  where ξ_{ub} denotes the useful portion of the signal received by u from b (see [RHE08] for the detailed calculation)

- For a multicast group $\mathcal{U}$ of N users served by cells in S, the average SINR is :

$$\bar{\gamma}_{\mathcal{U}}(S) = \frac{1}{N} \sum_{u \in \mathcal{U}} \gamma_u(S). \tag{2}$$

Dynamic Traffic Model

- Call blocking model : group of users arrive in the synchronization area, use a resource for a group communication for a certain duration and leave the system.
- Poisson arrival (λ), exponential service duration (μ), R resources in every BS.
- When a group arrives in the system, it is served by a subset S of BSs with probability p_S and one resource is consumed in every BS in S.
- We can approximate the blocking probability in BS b by using Erlang-B :

$$\tilde{\Pi}(b) \approx E_B(b, R) = \frac{\frac{\rho_b^R}{R!}}{\sum_{r=0}^{R} \frac{\rho_b^r}{r!}}, \tag{3}$$

where ρ_b is the load in station b (depends on λ, μ and the probability mass function p_S).

Problem Formulation : Cell Clustering

Cell clustering (inner) problem : find a minimizer set S that solves the following set function minimization problem, for a given group $\mathcal{U}$:

$$\min_{S \in \mathcal{P}_v} \Psi_{\mathcal{U}}(S) \triangleq w(S) - \bar{\gamma}_{\mathcal{U}}(S) \tag{4}$$

- S : set of serving BSs
- $\mathcal{P}_V$: set of all subsets of V
- $w(S) = \sum_{b \in S} w_b$: sum of the weights of BSs $b \in S$
- $\bar{\gamma}_{\mathcal{U}}(S)$: average SINR of group $\mathcal{U}$ served by cells in S

$\Rightarrow$ For a fixed $w = (w_1, \cdots, w_n) \in \mathbb{R}^n$, the traffic demand and the clustering policy p_S induces a blocking probability $\tilde{\Pi}(b; w)$ in every b

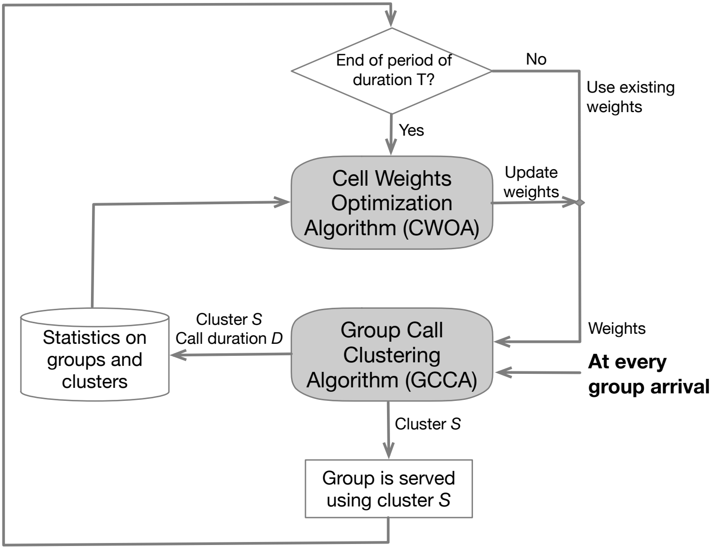
Problem Formulation : Weights Optimization

Weights optimization (outer) problem : find a minimizer of the quadratic error of the blocking probability wrt target blocking probabilities :

$$\min_{w \in \mathbb{R}^n} G(w) \triangleq \sum_{b=1}^{n} \left\| \tilde{\Pi}(b; w) - \bar{\Pi}(b) \right\|^2 \tag{5}$$

- $\tilde{\Pi}(b; w)$: blocking probability in a BS b that depend on the weights vector (w)
- $\bar{\Pi}(b)$: target blocking probability that BS b should attain

Dynamic Clustering Algorithm (DCA)

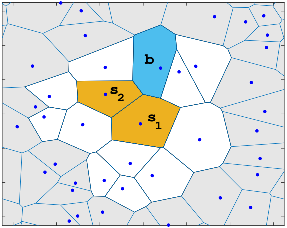


Group Call Cell Clustering Algorithm (GCCA)

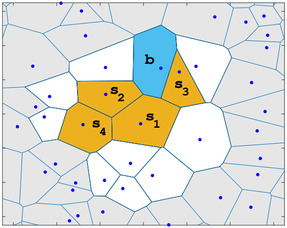
$$\min_{S \in \mathcal{P}_v} \Psi_{\mathcal{U}}(S) \triangleq w(S) - \bar{\gamma}_{\mathcal{U}}(S)$$

$\Psi_{\mathcal{U}}$ is a submodular function.

Submodular functions : A set function $F : 2^V \mapsto \mathbb{R}$ is submodular if and only if, for all subsets $A, B \subseteq V$ and $b \in V$ such that $A \subseteq B$ and $b \notin B$, we have : $F(A \cup b) - F(A) \geq F(B \cup b) - F(B)$.



Adding b to set $A = \{s_1, s_2\}$



Adding b to set $B = \{s_1, \ldots, s_4\}$

Group Call Cell Clustering Algorithm (GCCA)

$$\min_{S \in \mathcal{P}_v} \Psi_{\mathcal{U}}(S) \triangleq w(S) - \bar{\gamma}_{\mathcal{U}}(S)$$

$\Psi_{\mathcal{U}}$ is a submodular function.

- Minimizing $\Psi_{\mathcal{U}}$ is a **submodular minimization** problem.
- This problem is solved using the Minimum-Norm Algorithm [Fuj84, Wol76].
- The performance of this solution is compared to a Greedy based approach.

Cell Weights Optimization Algorithm (CWOA)

$$\min_{w \in \mathbb{R}^n} G(w) \triangleq \sum_{b=1}^{n} \left\| \tilde{\Pi}(b; w) - \bar{\Pi}(b) \right\|^2$$

- We rely on direct search methods to minimize G.
- These methods provide simpler calculations and relatively low storage requirements over derivative based methods.
- The most popular is the Nelder-Mead simplex method.

Cell Weights Optimization Algorithm (CWOA)

$$\min_{w \in \mathbb{R}^n} G(w) \triangleq \sum_{b=1}^{n} \|\tilde{\Pi}(b; w) - \bar{\Pi}(b)\|^2$$

- Nelder-Mead algorithm can stagnate, fail to converge or converge to a non-optimal vertex.
- A possible improvement of the original algorithm is to impose restarts of the algorithm during the optimization run.
- An oriented restart of the Nelder-Mead algorithm adapted to our model :
    - If $\tilde{\Pi}(b; w)$ is too small, weight w_b is decreased randomly ;
    - If $\tilde{\Pi}(b; w) > \bar{\Pi}(b)$, weight w_b is increased randomly.

Numerical Results : Group Call Clustering

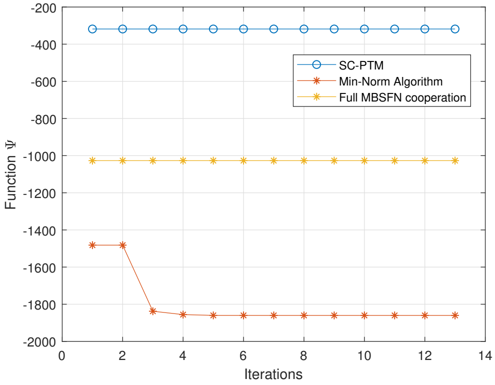
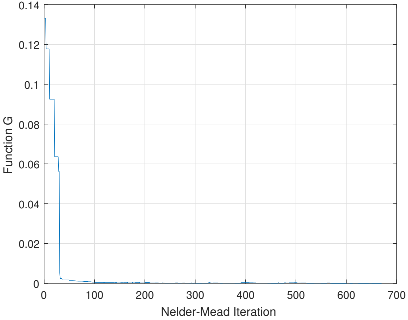
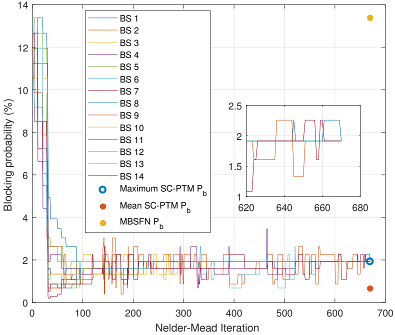


Figure – Evolution of $\Psi_{\mathcal{U}}$ along the iterations of the minimum-norm algorithm

SC-PTM and full MBSFN cooperation schemes are outperformed by the proposed algorithm in very few iterations.

Numerical Results : Cell Weights Optimization

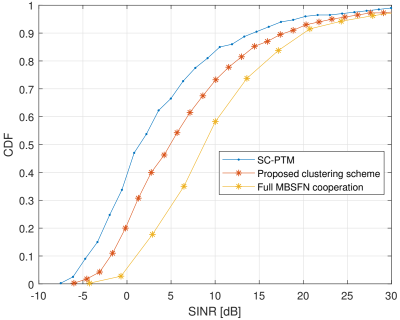


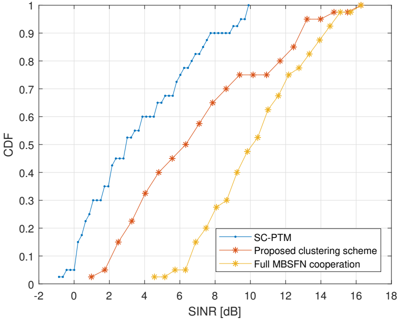


Evolution of G and cell blocking probabilities along the iterations of the Nelder-Mead algorithm

The reliability-capacity tradeoff is well handled by the proposed scheme.

Numerical Results : SINR Improvements





Users and group mean SINR CDF

The proposed scheme lies in-between MBSFN and SC-PTM in terms of SINR.

Conclusion

⇒ Our algorithm is able to adapt to traffic variations by maximizing the coverage under the constraint of a blocking probability.

Related publications :

- A. Daher, M. Coupechoux, P. Godlewski, P. Ngouat, P. Minot, A Dynamic Clustering Algorithm for Multi-Point Transmissions in Mission-Critical Communications in Mission-Critical Communications, IEEE Trans. on Wireless Communications, Apr. 2020.
- Alaa Daher, M. Shabbir Ali, Marceau Coupechoux, Philippe Godlewski, Pierre Ngouat, Pierre Minot, A Repetition Scheme for MBSFN Based Mission-Critical Communications, IEEE VTC Fall, Aug. 2018.
- A. Daher, M. Coupechoux, P. Godlewski, J.M. Kélif, P. Ngouat, P. Minot, SINR Model for MBSFN Based Mission Critical Communications, IEEE VTC Fall, Sept. 2017.
- A. Daher, M. Coupechoux, P. Godlewski, P. Ngouat, P. Minot, SC-PTM or MBSFN for Mission Critical Communications ?, IEEE VTC Spring, June 2017.

Outline

Motivation

- The previous study is ignoring security aspects and relies on simple physical layer models.

$\Rightarrow$ Our goal now : design a multi-BS multi-antenna transceiver for MCC that is robust to CSI errors (*reliability requirement of MCC*) and that is secured with respect to the presence of multiple eavesdroppers (*security*).

- Specifically, we incorporate security in two ways :
  - MIMO beamforming is used to achieve the desired performance gain at legitimate users while degrading eavesdroppers channel ;
  - Artificial Noise (AN) is added at the transmitter to guarantee additional security over the designed transceivers.
- Robustness is considered wrt :
  - Stochastic errors
  - Norm-bounded errors

Network Model

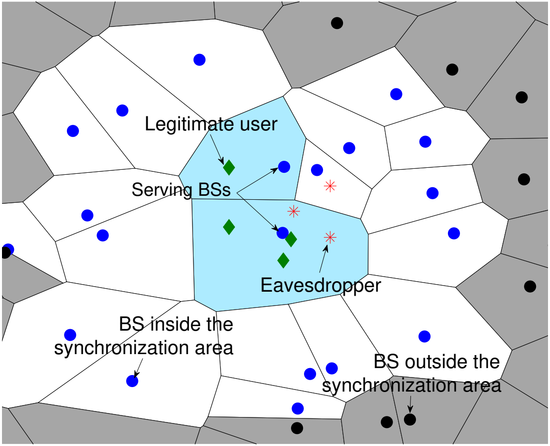


Figure – Blue cells are serving a group of legitimate users (green diamonds); multiple eavesdroppers may overhear the communication (red stars).

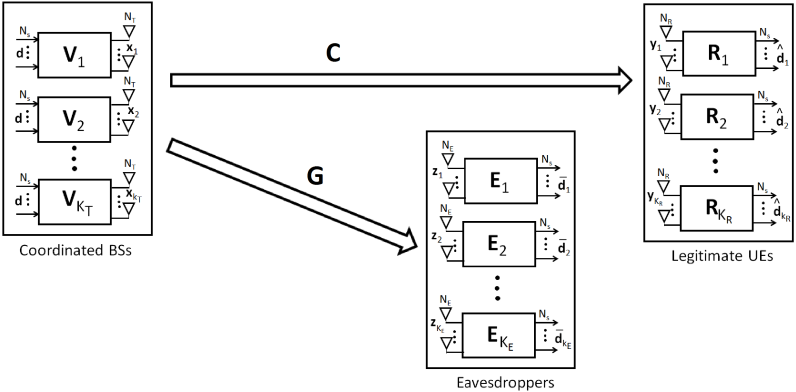
Network Model

A greedy clustering is adopted for simplicity :

Algorithm 1 Greedy Clustering

```
Input : Locations of BSs and group users, K'_T ≤ |B| : minimum cluster size
Init : S ← ∅
for every user do
    Find the BS t providing the highest receive power
    S ← S ∪ {t}
end for
if |S| < K'_T then
    Find the set S' of K'_T − |S| BSs maximizing the sum SINR for group users
    S ← S ∪ S'
end if
return S
```

Transceiver Model



Transceiver Model

- The signal transmitted from t-th BS is given by :

$$\mathbf{x}_t = \mathbf{V}_t \mathbf{d} + \mathbf{W}_t \mathbf{z}_t, \tag{6}$$

where $\mathbf{V}_t$ is a precoder, $\mathbf{z}_t$ is an zero-mean additional AN vector with variance $\mathbb{E}[\mathbf{z}_t \mathbf{z}_t^H] = \sigma_{zt}^2 \mathbf{I}_{N_T}$ and $\mathbf{W}_t$ is an AN-shaping matrix.

- The estimated data at user l is :

$$\widehat{\mathbf{d}}_l = \mathbf{R}_l \mathbf{C}_{tl} \mathbf{V}_t \mathbf{d} + \mathbf{R}_l \mathbf{C}_{tl} \mathbf{W}_t \mathbf{z}_t + \mathbf{R}_l \mathbf{n}_l. \tag{7}$$

where $\mathbf{R}_l$ is a receive filter.

- The MSE at the l-th legitimate UE is :

$$\epsilon_l \triangleq \mathbb{E}[||\mathbf{d} - \widehat{\mathbf{d}}_\mathbf{l}||^2], \tag{8}$$

- In the same way, the MSE at eavesdropper e is :

$$\epsilon_e \triangleq \mathbb{E}[||\mathbf{d} - \bar{\mathbf{d}}_\mathbf{e}||^2]. \tag{9}$$

Transceiver Model

CSI errors :

- At legitimate users : $\mathbf{G}_{te} = \widehat{\mathbf{G}}_{te} + \mathbf{\Delta}_{te}$
- At eavesdroppers : $\mathbf{C}_{tl} = \widehat{\mathbf{C}}_{tl} + \mathbf{\Delta}_{tl}$

Assumption (Stochastic error model)

CSI errors $\mathbf{\Delta}_{te}$ and $\mathbf{\Delta}_{tl}$ are modeled as Gaussian random variables such that $\mathbb{E}[\mathbf{\Delta}_{te}\mathbf{\Delta}_{te}^H] = \sigma_{te}^2\mathbf{I}$ and $\mathbb{E}[\mathbf{\Delta}_{tl}\mathbf{\Delta}_{tl}^H] = \sigma_{tl}^2\mathbf{I}$.

Assumption (Norm-bounded error model)

CSI errors $\mathbf{\Delta}_{te}$ and $\mathbf{\Delta}_{tl}$ are respectively taken in continuous sets, called uncertainty regions :

$$\mathcal{G}_{te} = \{\mathbf{\Delta}_{te} : ||\mathbf{\Delta}_{te}||^2 \leq \tau_{te}\}, \quad (10)$$

$$\mathcal{C}_{tl} = \{\mathbf{\Delta}_{tl} : ||\mathbf{\Delta}_{tl}||^2 \leq \tau_{tl}\}, \quad (11)$$

where τ_{te} and τ_{tl} denote the radii of the uncertainty regions.

Stochastic Errors : Problem Formulation

In presence of stochastic errors :

$$
\begin{aligned}
\underset{\substack{\mathbf{V}_t,\mathbf{W}_t,\mathbf{R}_l\\ t=1\ldots K_T,\, l=1\ldots K_R}}{\text{minimize}} \quad & \sum_{l=1}^{K_R} \epsilon_l, \\
\text{subject to} \quad & C1: \;\; \epsilon_e \geq \Gamma, \qquad \forall e \in \{1,\cdots,K_E\}, \\
& C2: \;\; P_t \leq P_T, \qquad \forall t \in \{1,\cdots,K_T\},
\end{aligned}
\tag{$\mathcal{P}_1$}
$$

where Γ is a design parameter that represents a lower bound on the achievable MSE expected at each eavesdropper.

Stochastic Errors : Stationary Point

Proposition

$$\mathbf{V}_t = (\mathbf{A}_t)^{-1}\left(\sum_{l=1}^{K_R}\widehat{\mathbf{C}}_{tl}^H\mathbf{R}_l^H - \sum_{e=1}^{K_E}\lambda_e\widehat{\mathbf{G}}_{te}^H\mathbf{E}_e^H\right) \quad (12)$$

$$\mathbf{W}_t = \mathbf{B}_t/\sqrt{[\mathrm{tr}(\mathbf{B}_t\mathbf{B}_t^{\mathrm{H}})]} \quad (13)$$

$$\mathbf{R}_l = \left(\sum_{t=1}^{K_T}\mathbf{V}_t^H\widehat{\mathbf{C}}_{tl}^H\right)\left(\sum_{t=1}^{K_T}\widehat{\mathbf{C}}_{tl}\mathbf{V}_t\mathbf{V}_t^H\widehat{\mathbf{C}}_{tl}^H + \sum_{t=1}^{K_T}\sigma_{zt}^2\widehat{\mathbf{C}}_{tl}\mathbf{W}_t\mathbf{W}_t^H\widehat{\mathbf{C}}_{tl}^H + \sigma_{nl}^2\mathbf{I} + \sum_{t=1}^{K_T}\sigma_{tl}^2\mathrm{tr}(\mathbf{V}_t\mathbf{V}_t^H)\mathbf{I} + \sum_{t=1}^{K_T}\sigma_{tl}^2\sigma_{zt}^2\mathrm{tr}(\mathbf{W}_t\mathbf{W}_t^H)\mathbf{I}\right)^{-1} \quad (14)$$

$$\mathbf{B}_t = \mathbf{I} - \mathbf{A}_t^H(\mathbf{A}_t\mathbf{A}_t^H)^{-1}\mathbf{A}_t,$$

$$\mathbf{A}_t = \sum_{l=1}^{K_R}\widehat{\mathbf{C}}_{tl}^H\mathbf{R}_l^H\mathbf{R}_l\widehat{\mathbf{C}}_{tl} + \sum_{l=1}^{K_R}\sigma_{tl}^2\mathrm{tr}(\mathbf{R}_l\mathbf{R}_l^H) - \sum_{e=1}^{K_E}\lambda_e\widehat{\mathbf{G}}_{te}^H\mathbf{E}_e^H\mathbf{E}_e\widehat{\mathbf{G}}_{te} - \sum_{e=1}^{K_E}\lambda_e\sigma_{te}^2\mathrm{tr}(\mathbf{E}_e\mathbf{E}_e^H) + \lambda_t^{'}\mathbf{I}.$$

Stochastic Errors : Block Descent Algorithm

Algorithm 2 Block Descent Algorithm

Input : β, K_T, K_R, K_E, $\widehat{\mathbf{C}}_{tl}$, $\widehat{\mathbf{G}}_{te}$, σ_{nl}, σ_{ne}, P_t $\forall$ $t \in \{1, \cdots, K_T\}$, $l \in \{1, \cdots, K_R\}$, and $e \in \{1, \cdots, K_E\}$
Init : Randomly generate $\mathbf{V}_t$, $\mathbf{W}_t$ $\forall t \in \{1, \cdots, K_T\}$, $\epsilon_l' \leftarrow 0$, $\epsilon_l \leftarrow 0$, $\forall l \in \{1, \cdots, K_R\}$
repeat
    $\epsilon_l' \leftarrow \epsilon_l$, $\forall l \in \{1, \cdots, K_R\}$
    Update $\mathbf{E}_e$ $\forall e \in \{1, \cdots, K_E\}$ (MMSE filter)
    Update $\mathbf{R}_l$ using $\mathbf{V}_t$, $\mathbf{W}_t$ in (14) $\forall l \in \{1, \cdots, K_R\}$
    Solve for λ_e and $\lambda_t^{'}$ using $C1$, $C2$ $\forall t \in \{1, \cdots, K_T\}$, and $\forall e \in \{1, \cdots, K_E\}$
    Update $\mathbf{V}_t$ using λ_e, $\lambda_t^{'}$, $\mathbf{R}_l$, $\mathbf{E}_e$ in (12) $\forall t = \{1, \cdots, K_T\}$
    Update $\mathbf{W}_t$ using $\mathbf{V}_t$ in (13) $\forall t = \{1, \cdots, K_T\}$
    Compute ϵ_l using $\mathbf{V}_t$, λ_e, $\lambda_t^{'}$, $\mathbf{W}_t$, and $\mathbf{R}_l$
until $|\epsilon_l - \epsilon_l'| \leq \beta$, $\forall l \in \{1, \cdots, K_R\}$
return $\mathbf{V}_t$, $\mathbf{W}_t$, $\forall t \in \{1, \cdots, K_T\}$, $\mathbf{R}_l$, ϵ_l $\forall l \in \{1, \cdots, K_R\}$

Norm-Bounded Errors : Problem Formulation

In presence of norm-bounded errors :

$$\begin{aligned}
\underset{\substack{\mathbf{V}_t,\mathbf{W}_t,\mathbf{R}_l \\ t=1\ldots K_T, l=1\ldots K_R}}{\text{minimize}} \quad & \sum_{l=1}^{K_R} \epsilon_l, \\
\text{subject to} \quad & C1, C2 \\
& C4: \ \boldsymbol{\Delta}_{te} \in \mathcal{G}_{te}, \qquad \forall t \in \{1, \cdots, K_T\}, \forall e \in \{1, \cdots, K_E\} \\
& C5: \ \boldsymbol{\Delta}_{tl} \in \mathcal{C}_{tl}, \qquad \forall t \in \{1, \cdots, K_T\}, \forall l \in \{1, \cdots, K_R\}
\end{aligned} \tag{$\mathcal{P}_2$}$$

An equivalent (robust) formulation :

$$\begin{aligned}
\underset{\substack{\mathbf{V}_t,\mathbf{W}_t,\mathbf{R}_l \\ t=1\ldots K_T, l=1\ldots K_R}}{\text{minimize}} \quad & \max_{\boldsymbol{\Delta}_{tl} \in \mathcal{C}_{tl}} \sum_{l=1}^{K_R} \epsilon_l, \\
\text{subject to} \quad & C2, \\
& C6: \ \min_{\boldsymbol{\Delta}_{te} \in \mathcal{G}_{te}} \epsilon_e \geq \Gamma, \qquad \forall e \in \{1, \cdots, K_E\}
\end{aligned} \tag{$\bar{\mathcal{P}}_2$}$$

Norm-Bounded Errors : Problem Decomposition

Sub-problem $\bar{\mathcal{P}}_2'$: Assume that the worst-case channel errors $\mathbf{\Delta}_{te}$ and $\mathbf{\Delta}_{tl}$ are known and solve for the transceiver matrices :

$$\begin{aligned} \underset{\substack{\mathbf{V}_t,\mathbf{W}_t,\mathbf{R}_l \\ t=1\ldots K_T, l=1\ldots K_R}}{\text{minimize}} \quad & \sum_{l=1}^{K_R} \epsilon_l, \\ \text{subject to} \quad & C1, C2 \end{aligned} \qquad (\bar{\mathcal{P}}_2')$$

Sub-problem $\bar{\mathcal{P}}_2''$: Assume that transceiver matrices and the worst-case error $\mathbf{\Delta}_{te}$ are known and solve for the worst-case error $\mathbf{\Delta}_{tl}$.

$$\begin{aligned} \underset{\substack{\mathbf{\Delta}_{tl} \\ t=1\ldots K_T, l=1\ldots K_R}}{\text{minimize}} \quad & -\sum_{l=1}^{K_R} \epsilon_l, \\ \text{subject to} \quad & C5 : ||\mathbf{\Delta}_{tl}||^2 \leq \tau_{tl} \qquad \forall t \in \{1,\cdots,K_T\}, \forall l \in \{1,\cdots,K_R\} \end{aligned} \qquad (\bar{\mathcal{P}}_2'')$$

Norm-Bounded Errors : Problem Decomposition

Sub-problem $\bar{\mathcal{P}}_2'''$: Assume that transceiver matrices and the worst-case error $\mathbf{\Delta}_{tl}$ are known and solve for the worst-case error $\mathbf{\Delta}_{te}$.

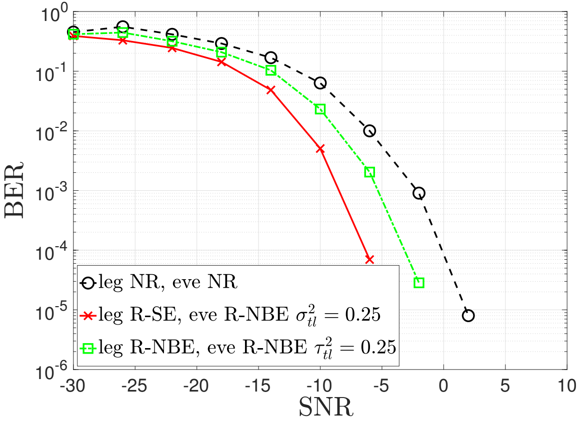
$$\begin{aligned} &\underset{\mathbf{\Delta}_{te}, t=1\ldots K_T}{\text{minimize}} && \epsilon_e \geq \Gamma, \\ &\text{subject to} && C4 : ||\mathbf{\Delta}_{te}||^2 \leq \tau_{te} \qquad \forall t \in \{1, \cdots, K_T\} \end{aligned} \tag{$\bar{\mathcal{P}}_2'''$}$$

Norm-Bounded Errors : Algorithm

Algorithm 3 Iterative Algorithms for NBE

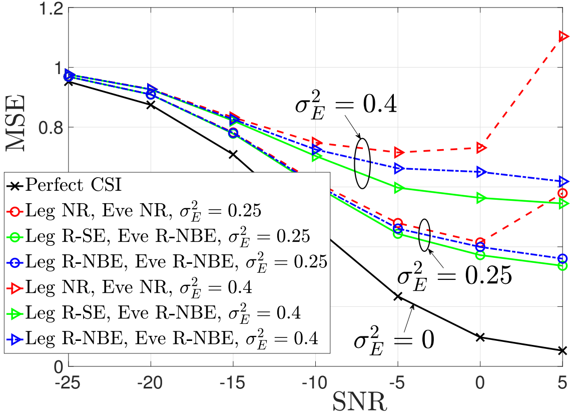
1: **Input :** β, K_T, K_R, K_E, $\mathbf{E}_e$, $\widehat{\mathbf{C}}_{tl}$, $\widehat{\mathbf{G}}_{te}$, τ_{tl}, τ_{te}, P_t, $\forall\ t \in \{1, \cdots, K_T\}$, $l \in \{1, \cdots, K_R\}$, and $e \in \{1, \cdots, K_E\}$
2: **Init :** Randomly generate $\mathbf{V}_t$, $\mathbf{W}_t$, $\forall t \in \{1, \cdots, K_T\}$, $\boldsymbol{\Delta}_{tl} \in \mathcal{C}_{tl}$, $\boldsymbol{\Delta}_{te} \in \mathcal{G}_{te}$, $\epsilon_l \leftarrow 0$, $\forall t \in \{1, \cdots, K_T\}$, $l \in \{1, \cdots, K_R\}$, $e \in \{1, \cdots, K_E\}$,
3: **repeat**
4: $\quad \epsilon_l' \leftarrow \epsilon_l$, $\forall l \in \{1, \cdots, K_R\}$
5: $\quad$ Solve $\bar{\mathcal{P}}_2'$ and update $\mathbf{V}_t$, $\mathbf{W}_t$, $\mathbf{R}_l$ using $\boldsymbol{\Delta}_{tl}$, $\boldsymbol{\Delta}_{te}$, $\mathbf{E}_e$ and Algorithm 2 $\forall t \in \{1, \cdots, K_T\}$, $l \in \{1, \cdots, K_R\}$, $e \in \{1, \cdots, K_E\}$
6: $\quad$ Solve $\bar{\mathcal{P}}_2''$ and update $\boldsymbol{\Delta}_{tl}$ using $\mathbf{V}_t$, $\mathbf{W}_t$, $\mathbf{R}_l$ $\forall t \in \{1, \cdots, K_T\}$, $l \in \{1, \cdots, K_R\}$
7: $\quad$ Solve $\bar{\mathcal{P}}_2'''$ and update $\boldsymbol{\Delta}_{te}$ using $\mathbf{V}_t$, $\mathbf{W}_t$, $\mathbf{E}_e$ $\forall t \in \{1, \cdots, K_T\}$, $e \in \{1, \cdots, K_E\}$
8: $\quad$ Compute ϵ_l using $\mathbf{V}_t$, $\mathbf{W}_t$, and $\mathbf{R}_l$, $\boldsymbol{\Delta}_{tl}$, $\boldsymbol{\Delta}_{te}$
9: **until** $|\epsilon_l - \epsilon_l'| \leq \beta$, $\forall l \in \{1, \cdots, K_R\}$

Numerical Results : Physical Layer



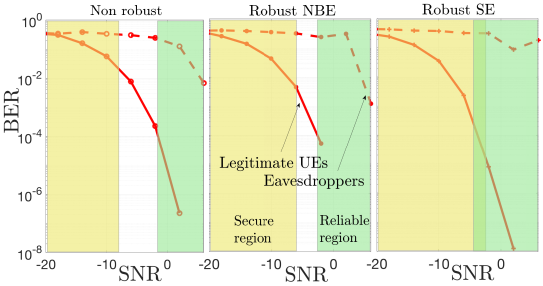
- Robust design improves the reliability of MCC.
- Due to increased uncertainty, norm-bounded errors leads to poorer performances compared to stochastic errors.

Numerical Results : Physical Layer



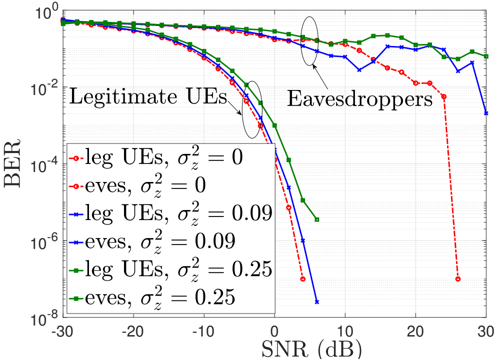
- System performance decreases with increasing CSI error variance.
- The higher the variance, the higher the gap bw robust and non-robust.

Numerical Results : Physical Layer



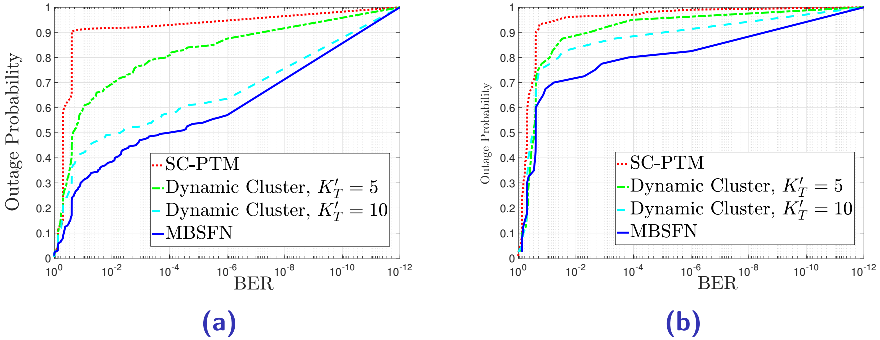
- Security gap : $S_g = SNR^L_{min} - SNR^E_{max}$
- Below SNR^E_{max} at eavesdroppers, the communication is secure, above SNR^L_{min} at legitimate UEs, the communication is reliable.
- NR : 4dB, R-NBE : 2dB, R-SE : -2dB at BER 10^{-4} for leg. UEs and 0.3 for eaves
- Robust designs achieve reduced security gap (enhanced secrecy performance).

Physical Level Simulation Results



- Presence of AN degrades the performance at eavesdropper whereas it has a very low impact on BER of legitimate UE.

Numerical Results : System Level



- All the systems, MBSFN, SC-PTM and dynamic clustering demonstrate enhanced performance for legitimate UEs as compared to eavesdroppers.
- At legitimate UEs, MBSFN performs the best, SC-PTM performs worst, whereas dynamic clustering shows a good trade off.

Conclusion

$\Rightarrow$ We designed an efficient multi-BS multi-antenna secure MIMO transceiver that meets the unique requirements of MCC.

Related publications :

- Deepa Jagyasi, Marceau Coupechoux, Secure Transceiver Design for Multi-user MIMO Multicast Mission Critical Communication System, *submitted*.
- Deepa Jiagyasi, Alaa Daher, Marceau Coupechoux, Multicell MIMO Transceiver Design for Mission-Critical Communication, IEEE Globecom, Dec. 2019.

Outline

Conclusions and Future Works

- Mission critical communications for public safety, critical infrastructure, etc is a relatively unexplored topic.
- They deserve specific designs because of a unique set of joint constraints like security, reliability, coverage, multicast services.
- Traditional designs focusing on capacity and user data rate maximization no longer apply.
- Future works includes mm waves studies and new approaches to reduce energy consumption.

Thank you for your attention !

References I

- Paolo Baracca, Federico Boccardi, and Nevio Benvenuto, *A dynamic clustering algorithm for downlink CoMP systems with multiple antenna UEs*, EURASIP Journal on Wireless Communications and Networking (2014), 1–14.
- Selcuk Bassoy, Mona Jaber, Muhammad Ali Imran, and Pei Xiao, *Load Aware Self-Organising User-Centric Dynamic CoMP Clustering for 5G Networks*, IEEE Access **4** (2016), 2895–2906.
- Jiasi Chen, Mung Chiang, Jeffrey Erman, Guangzhi Li, K.K. Ramakrishnan, and Rakesh K. Sinha, *Fair and optimal resource allocation for LTE multicast (eMBMS) : Group partitioning and dynamics*, 2015 IEEE Conference on Computer Communications (INFOCOM), 2015, pp. 1266–1274.
- Yuhuan Du and Gustavo de Veciana, *"Wireless networks without edges" : Dynamic radio resource clustering and user scheduling*, 2014 IEEE Conference on Computer Communications (INFOCOM), 2014, pp. 1321–1329.
- Satoru Fujishige, *Submodular systems and related topics*, Mathematical Programming at Oberwolfach II, 1984, pp. 113–131.

References II

Virgile Garcia, Yiqing Zhou, and Jinglin Shi, *Coordinated Multipoint Transmission in Dense Cellular Networks With User-Centric Adaptive Clustering*, IEEE Transactions on Wireless Communications **13** (2014), no. 8, 4297–4308.

Dong Liu, Shengqian Han, Chenyang Yang, and Qian Zhang, *Semi-dynamic User-Specific Clustering for Downlink Cloud Radio Access Network*, IEEE Transactions on Vehicular Technology **65** (2016), 2063–2077.

Ling Liu, Yiqing Zhou, Virgile Garcia, Lin Tian, and Jinglin Shi, *Load Aware Joint CoMP Clustering and Inter-Cell Resource Scheduling in Heterogeneous Ultra Dense Cellular Networks*, IEEE Transactions on Vehicular Technology **67** (2018), 2741–2755.

A. Papadogiannis, D. Gesbert, and E. Hardouin, *A Dynamic Clustering Approach in Wireless Networks with Multi-Cell Cooperative Processing*, 2008 IEEE International Conference on Communications, 2008, pp. 4033–4037.

References III

- Letian Rong, Salah Eddine Elayoubi, and Olfa Ben Haddada, *Performance evaluation of cellular networks offering TV services*, IEEE Transactions on Vehicular Technology **60** (2011), no. 2, 644–655.
- Letian Rong, Olfa Ben Haddada, and Salah Eddine Elayoubi, *Analytical analysis of the coverage of a MBSFN OFDMA network*, GLOBECOM - IEEE Global Telecommunications Conference (2008), 2388–2392.
- Sebastian Scholz, *Combining dynamic clustering and scheduling for coordinated multi-point transmission in LTE*, 2017 IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC), 2017, pp. 1–7.
- Philip Wolfe, *Finding the nearest point in A polytope*, Mathematical Programming **11** (1976), no. 1, 128–149.
- Misun Yoon, Myoung-Seok Kim, and Chungyong Lee, *A Dynamic Cell Clustering Algorithm for Maximization of Coordination Gain in Uplink Coordinated System*, IEEE Transactions on Vehicular Technology **65** (2016), 1752–1760.

References IV

Zhe Zhang, Ning Wang, Jiankang Zhang, Xiaomin Mu, and Kon Max Wong, *Cooperation Resource Efficient User-Centric Clustering for QoS Provisioning in Uplink CoMP*, 2017 IEEE 18th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC), 2017, pp. 1–5.