

# BROADCAST APPROACH FOR THE SPARSE-INPUT RANDOM-SAMPLED MIMO GAUSSIAN CHANNEL

Antonia M. Tulino

Nokia Bell Labs, New Jersey, USA

Università di Napoli Federico II, Italy

# THE PROBLEM: MIMO BROADCAST

Random matrix with distribution discussed later on

$$\mathbf{y}_{p_i} = \underbrace{\mathbf{A}_{p_i} \mathbf{U} \mathbf{B}}_{N \times N} \mathbf{x} + \mathbf{z}$$

$$\mathbb{E}[\|\mathbf{x}\|^2] \leq P$$

where:

- $\mathbf{z} \sim \mathcal{CN}(\mathbf{0}, \mathbf{I})$

- $\mathbf{A} = \begin{pmatrix} A_{1,1} & 0 & \dots & 0 \\ 0 & A_{2,2} & 0 & \vdots \\ \vdots & 0 & \ddots & 0 \\ 0 & \dots & 0 & A_{N,N} \end{pmatrix}, \quad A_{j,j} \in \{0,1\} \quad \mathbb{P}[A_{j,j} = 1] = p_i$

Random with pdf  $w(p)$

$p_i \in (0, 1]$

- $\mathbf{B} = \begin{pmatrix} B_{1,1} & 0 & \dots & 0 \\ 0 & B_{2,2} & 0 & \vdots \\ \vdots & 0 & \ddots & 0 \\ 0 & \dots & 0 & B_{N,N} \end{pmatrix}, \quad B_{j,j} \in \{0,1\} \quad \mathbb{P}[B_{j,j} = 1] = q$

GIVEN AN INPUT SPARSITY, MAXIMIZE TOTAL MULTICAST RATE WITH CHANNEL PARAMETER DISTRIBUTED AS  $p \in (0,1] \sim W(p)$

# STOCHASTICALLY DEGRADED MIMO BROADCAST CHANNEL



$$\mathbf{y}_{p_1} = \mathbf{A}_{p_1} \mathbf{U} \mathbf{B} \mathbf{x} + \mathbf{z}$$



$$\mathbf{y}_{p_2} = \mathbf{A}_{p_2} \mathbf{U} \mathbf{B} \mathbf{x} + \mathbf{z}$$



The channel with sampling rate  $p_1$  is a stochastically degraded version of a channel with sampling rate  $p_2$  if:

$$p_1 \leq p_2$$

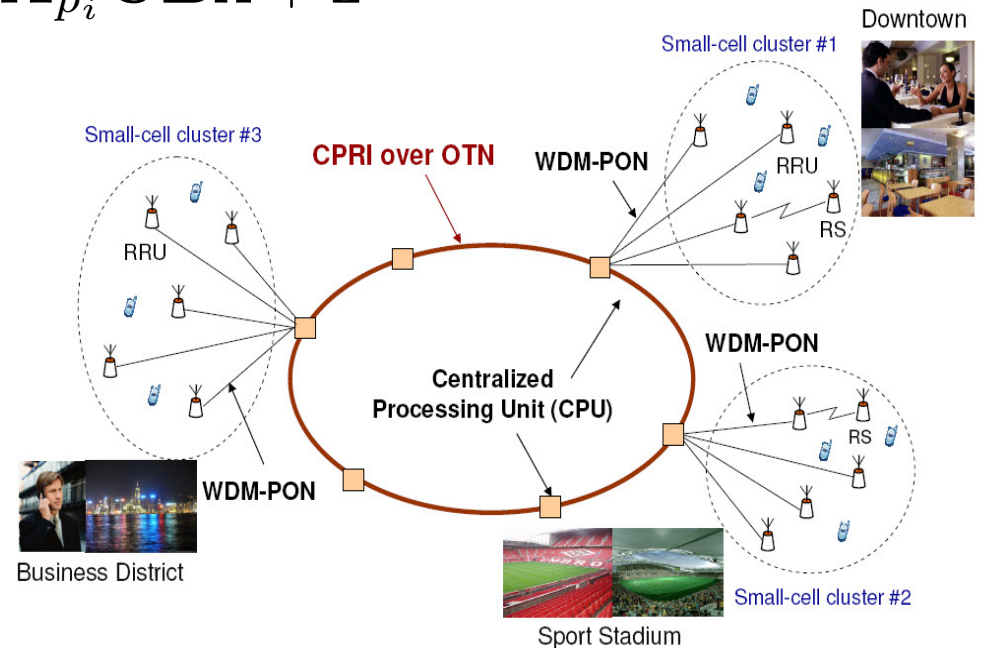
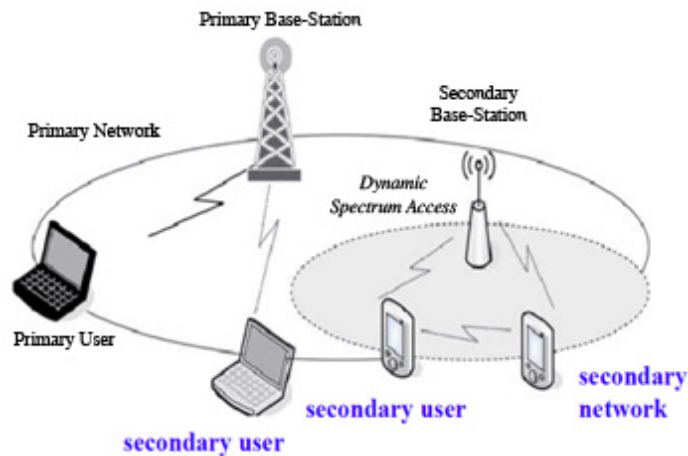
Our objective will be to maximize the total multicast average rate.

To do this we will resort to the *broadcast approach*

S. SHAMAI AND A. STEINER, "A BROADCAST APPROACH FOR A SINGLE-USER SLOWLY FADING MIMO CHANNEL," IEEE TRANS. ON INFORM. THEORY.

# MOTIVATIONS

$$\mathbf{y}_{p_i} = \mathbf{A}_{p_i} \mathbf{U} \mathbf{B} \mathbf{x} + \mathbf{z}$$



## OFDM-BASED COGNITIVE RADIO

OFDM with randomly sparse subcarrier aggregation:  
the non-zeros of  $\mathbf{B}$  are the subcarriers used for  
transmission;  $\mathbf{U}$  is a unitary DFT matrix,

## CLOUD RAN ARCHITECTURE

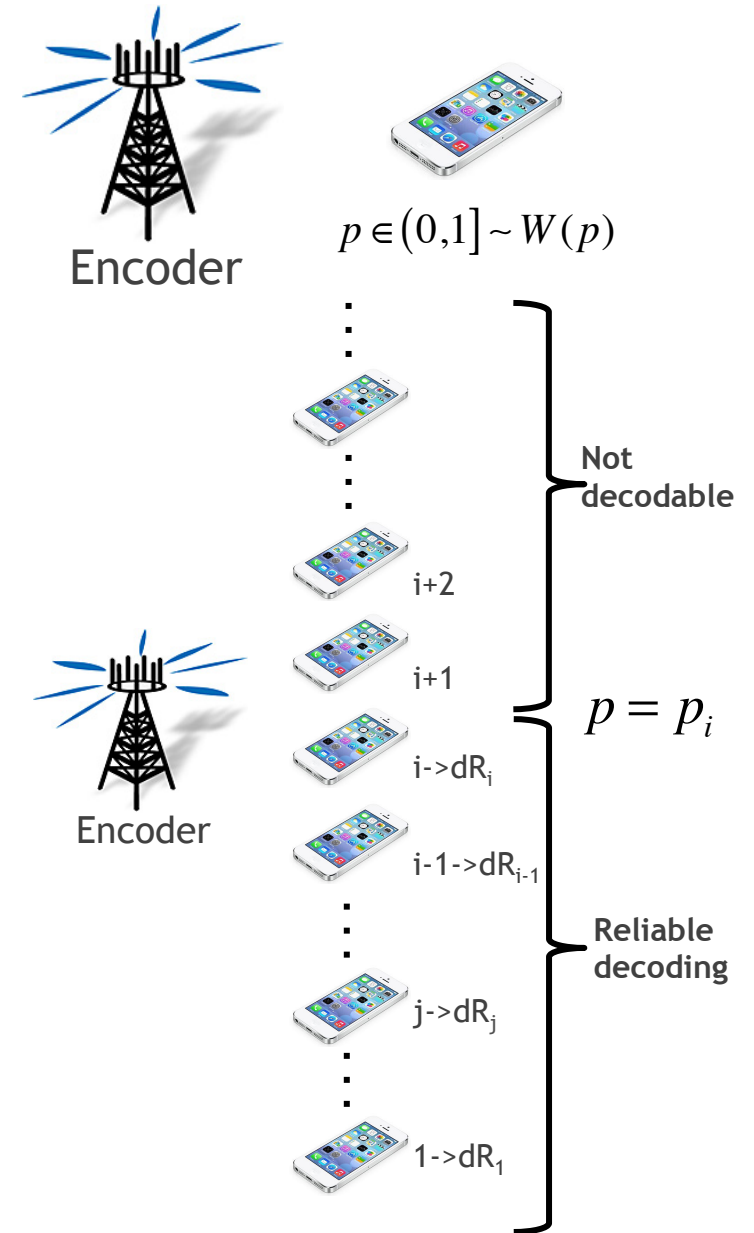
The CPU has no feedback on the status of the RRU:  
the non-zeros of  $\mathbf{B}$  are the RRU active;  $\mathbf{U}$  is a  
Gaussian matrix (iid for example.)

TRANSMITTER AWARE ONLY OF THE STATISTICS OF THE MATRIX  $\mathbf{AUB}$



# BROADCAST APPROACH

$$\mathbf{y}_p = \mathbf{A}_p \mathbf{U} \mathbf{B} \mathbf{x} + \mathbf{z};$$

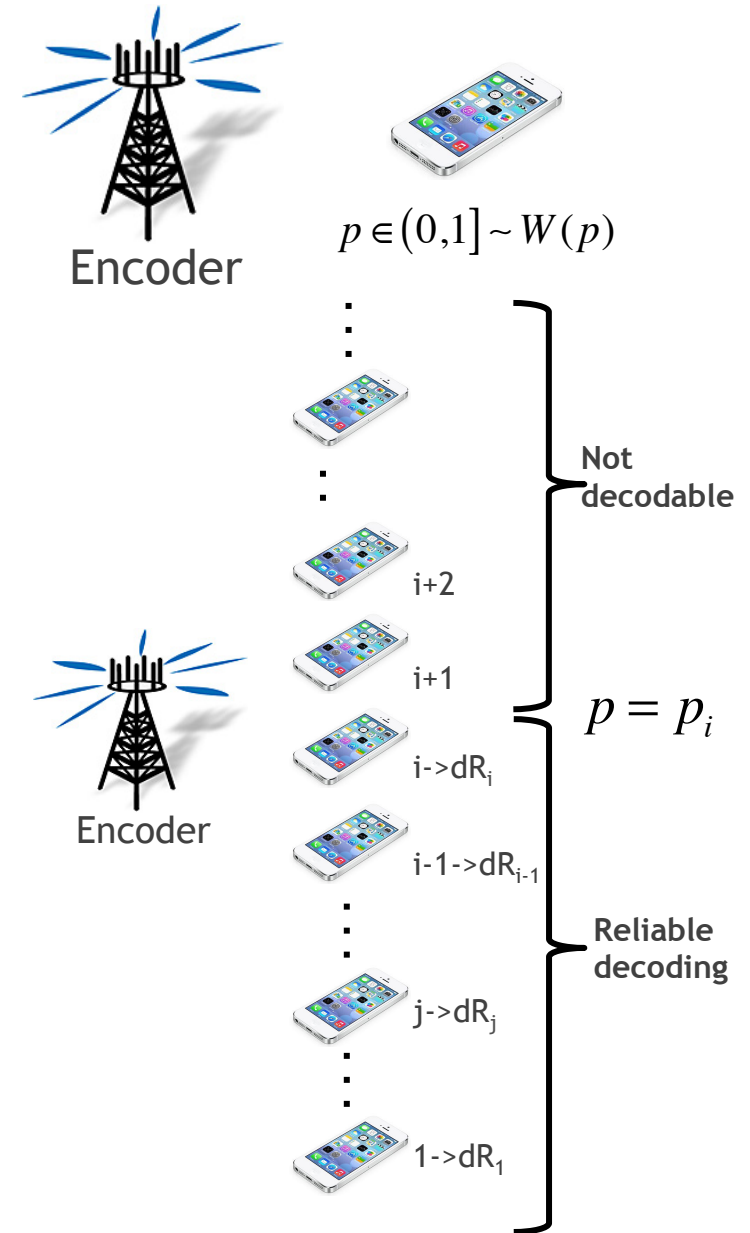


# BROADCAST APPROACH

$$\mathbf{y}_p = \mathbf{A}_p \mathbf{U} \mathbf{B} \mathbf{x} + \mathbf{z};$$

$$dR_j$$

$$R_i = \sum_{j \leq i} dR_j$$



# BROADCAST APPROACH

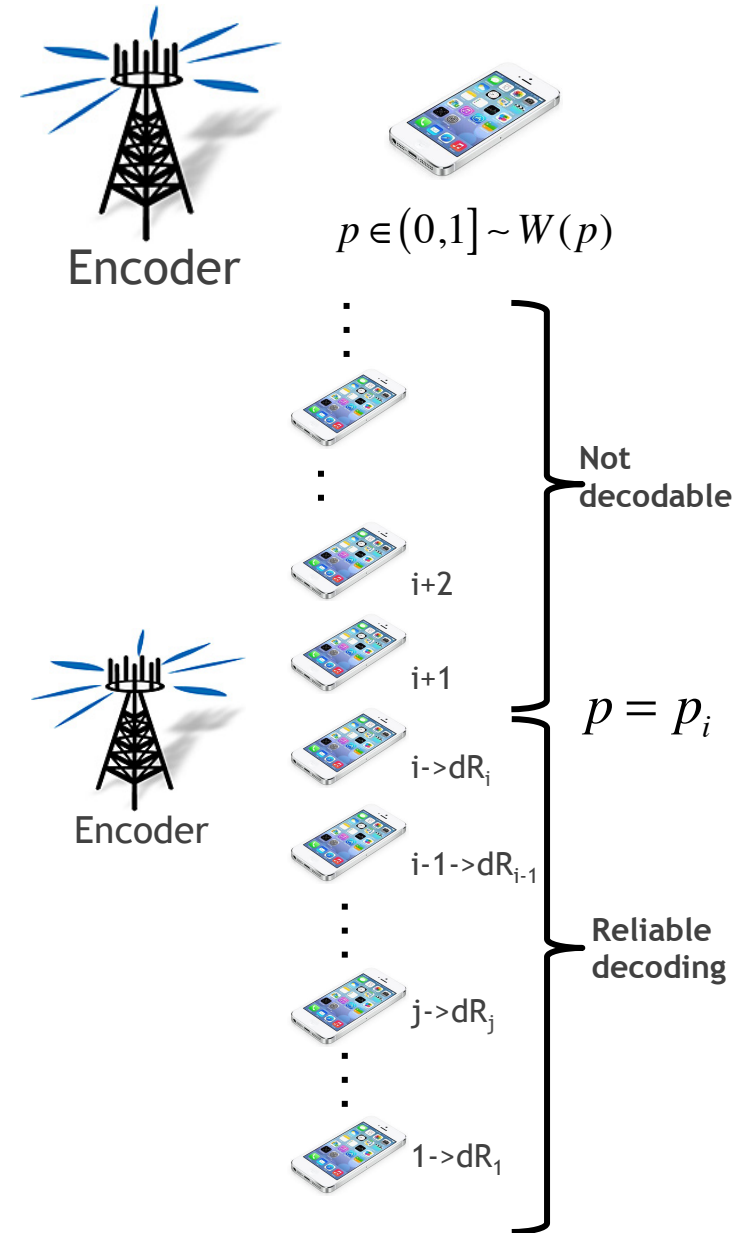
$$\mathbf{y}_p = \mathbf{A}_p \mathbf{U} \mathbf{B} \mathbf{x} + \mathbf{z};$$

$$dR_j$$

$$R_i = \sum_{j \leq i} dR_j$$

$$\sqrt{\mathbf{R}_p} \triangleq \mathbf{A}_p \mathbf{U} \mathbf{B}$$

$$\mathcal{V}_{\mathbf{R}_p}(\rho) \triangleq \frac{1}{N} \mathbb{E} [\log |\mathbf{I} + \rho \mathbf{R}_p|]$$



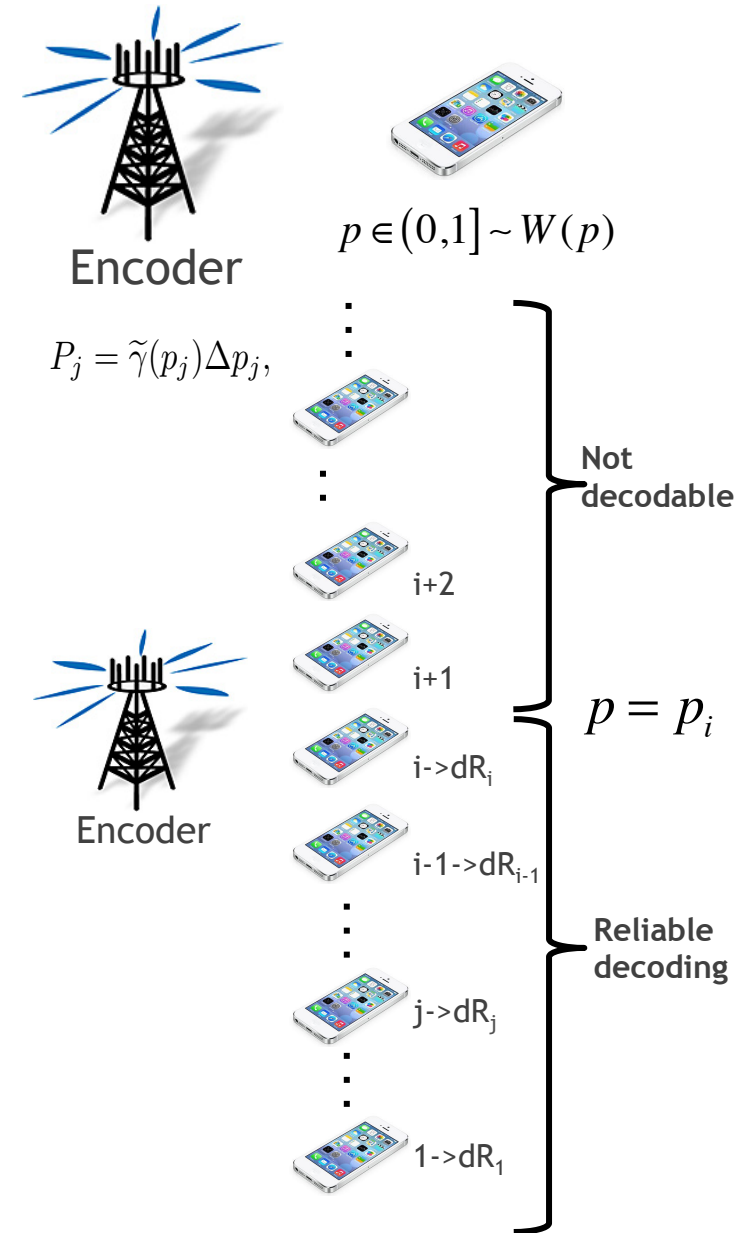
# BROADCAST APPROACH

$$\mathbf{y}_p = \mathbf{A}_p \mathbf{U} \mathbf{B} \mathbf{x} + \mathbf{z};$$

$$\begin{aligned} \sqrt{\mathbf{R}_p} &\triangleq \mathbf{A}_p \mathbf{U} \mathbf{B} \\ \mathcal{V}_{\mathbf{R}_p}(\rho) &\triangleq \frac{1}{N} \mathbb{E} [\log |\mathbf{I} + \rho \mathbf{R}_p|] \end{aligned}$$

$$dR_j = \mathcal{V}_{\mathbf{R}_{p_j}} \left( \sum_{k \geq j} \tilde{\gamma}(p_k) \Delta s_k \right) - \mathcal{V}_{\mathbf{R}_{p_j}} \left( \sum_{k > j} \tilde{\gamma}(p_k) \Delta s_k \right)$$

$$R_i = \sum_{j \leq i} dR_j$$



# BROADCAST APPROACH

$$\mathbf{y}_p = \mathbf{A}_p \mathbf{U} \mathbf{B} \mathbf{x} + \mathbf{z};$$

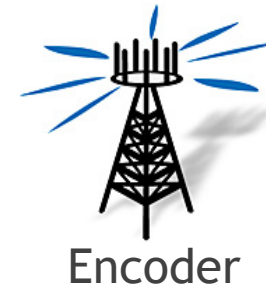
$$\begin{aligned} \sqrt{\mathbf{R}_p} &\triangleq \mathbf{A}_p \mathbf{U} \mathbf{B} \\ \mathcal{V}_{\mathbf{R}_p}(\rho) &\triangleq \frac{1}{N} \mathbb{E} [\log |\mathbf{I} + \rho \mathbf{R}_p|] \end{aligned}$$

$$dR_j = \mathcal{V}_{\mathbf{R}_{p_j}} \left( \sum_{k \geq j} \tilde{\gamma}(p_k) \Delta s_k \right) - \mathcal{V}_{\mathbf{R}_{p_j}} \left( \sum_{k > j} \tilde{\gamma}(p_k) \Delta s_k \right)$$

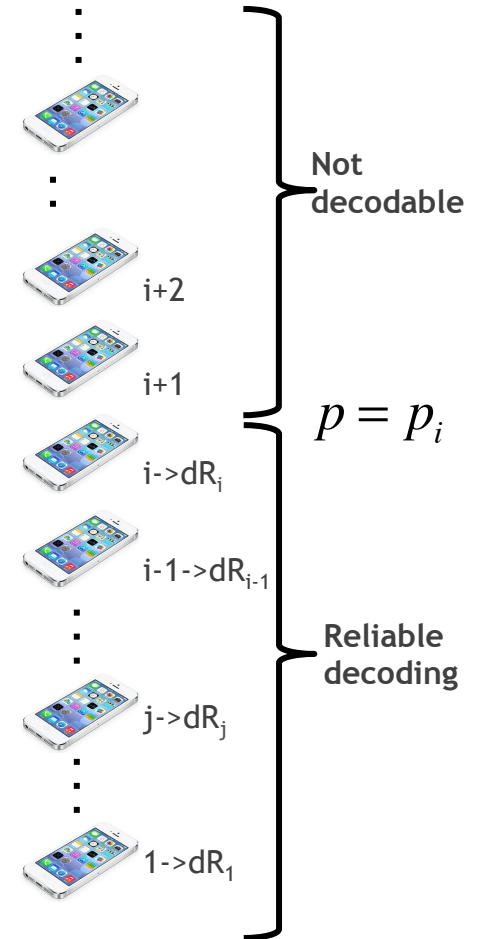
$$\approx \left. \frac{\partial}{\partial \rho} \mathcal{V}_{\mathbf{R}_{p_j}}(\rho) \right|_{\rho = \sum_{k > j} \tilde{\gamma}(p_k) \Delta p_k} \times \tilde{\gamma}(p_j) \Delta p_j.$$

$$\begin{aligned} P_j &= \tilde{\gamma}(p_j) \Delta p_j, \\ \Delta p_j &= p_j - p_{j-1}, \end{aligned}$$

$$R_i = \sum_{j \leq i} dR_j$$



$$p \in (0,1] \sim W(p)$$





# BROADCAST APPROACH

$$\mathbf{y}_p = \mathbf{A}_p \mathbf{U} \mathbf{B} \mathbf{x} + \mathbf{z};$$

$$\begin{aligned} \sqrt{\mathbf{R}_p} &\triangleq \mathbf{A}_p \mathbf{U} \mathbf{B} \\ \mathcal{V}_{\mathbf{R}_p}(\rho) &\triangleq \frac{1}{N} \mathbb{E} [\log |\mathbf{I} + \rho \mathbf{R}_p|] \end{aligned}$$

$$dR_j = \mathcal{V}_{\mathbf{R}_{p_j}} \left( \sum_{k \geq j} \tilde{\gamma}(p_k) \Delta s_k \right) - \mathcal{V}_{\mathbf{R}_{p_j}} \left( \sum_{k > j} \tilde{\gamma}(p_k) \Delta s_k \right)$$

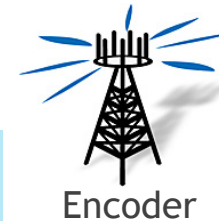
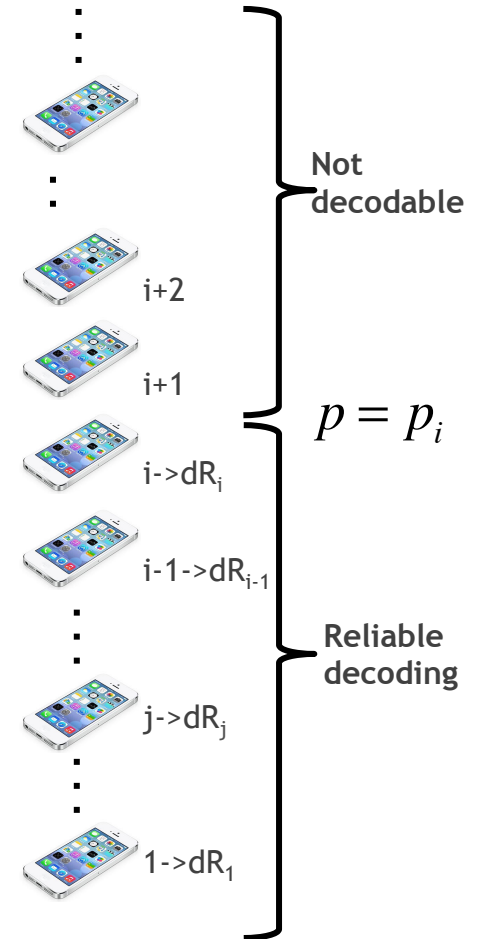
$$\approx \left. \frac{\partial}{\partial \rho} \mathcal{V}_{\mathbf{R}_{p_j}}(\rho) \right|_{\rho = \sum_{k > j} \tilde{\gamma}(p_k) \Delta p_k} \times \tilde{\gamma}(p_j) \Delta p_j.$$

$$\begin{aligned} P_j &= \tilde{\gamma}(p_j) \Delta p_j, \\ \Delta p_j &= p_j - p_{j-1}, \end{aligned}$$

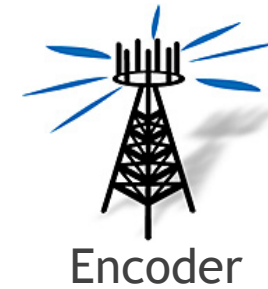
$$\begin{aligned} R_i &= \sum_{j \leq i} dR_j \\ &= \sum_{j \leq i} \left. \frac{\partial}{\partial \rho} \mathcal{V}_{\mathbf{R}_{p_j}}(\rho) \right|_{\rho = \sum_{k > j} \tilde{\gamma}(p_k) \Delta p_k} \times \tilde{\gamma}(p_j) \Delta p_j \end{aligned}$$



$$p \in (0,1] \sim W(p)$$



# BROADCAST APPROACH



$$p \in (0,1] \sim W(p)$$

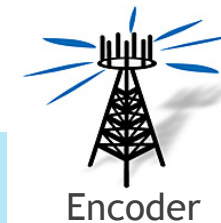
$$\mathbf{y}_p = \mathbf{A}_p \mathbf{U} \mathbf{B} \mathbf{x} + \mathbf{z};$$

$$\begin{aligned} \sqrt{\mathbf{R}_p} &\triangleq \mathbf{A}_p \mathbf{U} \mathbf{B} \\ \mathcal{V}_{\mathbf{R}_p}(\rho) &\triangleq \frac{1}{N} \mathbb{E} [\log |\mathbf{I} + \rho \mathbf{R}_p|] \end{aligned}$$

$$dR_j = \mathcal{V}_{\mathbf{R}_{p_j}} \left( \sum_{k \geq j} \tilde{\gamma}(p_k) \Delta s_k \right) - \mathcal{V}_{\mathbf{R}_{p_j}} \left( \sum_{k > j} \tilde{\gamma}(p_k) \Delta s_k \right)$$

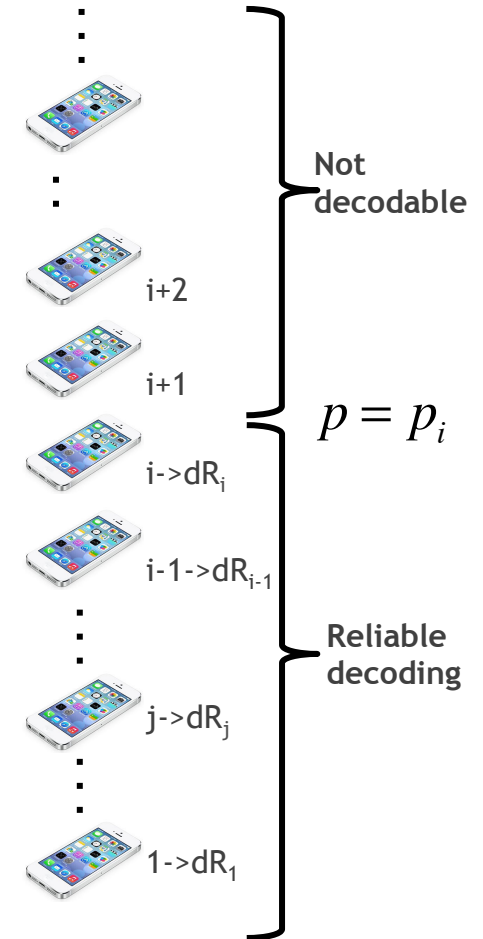
$$\approx \left. \frac{\partial}{\partial \rho} \mathcal{V}_{\mathbf{R}_{p_j}}(\rho) \right|_{\rho = \sum_{k > j} \tilde{\gamma}(p_k) \Delta p_k} \times \tilde{\gamma}(p_j) \Delta p_j.$$

$$\begin{aligned} P_j &= \tilde{\gamma}(p_j) \Delta p_j, \\ \Delta p_j &= p_j - p_{j-1}, \end{aligned}$$



$$R_i = \sum_{j \leq i} dR_j$$

$$\xrightarrow{\Delta p_j \rightarrow 0} \int_0^{p_i} \left. \frac{\partial}{\partial \rho} \mathcal{V}_{\mathbf{R}_a}(\rho) \right|_{\rho = \int_a^\infty \tilde{\gamma}(u) du} \tilde{\gamma}(a) da, \quad \gamma(a) = \begin{cases} \gamma(0) = P \\ \gamma(\infty) = 0 \end{cases}$$



# TOTAL MULTICAST RATE

$$\mathbf{R}_p \triangleq \mathbf{A}_p \mathbf{U} \mathbf{B} \mathbf{U}^H \mathbf{A}_p$$

The average rate achievable by the broadcast approach for a user with  $p \in (0,1] \sim W(p)$

$$\frac{1}{N} R = \frac{1}{N} \int_0^\infty w(p) R(p) dp = \int_0^\infty w(p) \int_0^p \frac{\partial}{\partial \rho} \mathcal{V}_{\mathbf{R}_p}(\rho) \Big|_{\rho=\gamma(p)} dp$$

Optimizing  $R$  with respect to  $\gamma(p)$  consists of maximizing

$$\frac{1}{N} R = \int_0^\infty (1 - W(p)) \frac{\partial}{\partial \rho} \mathcal{V}_{\mathbf{R}_p}(\rho) \Big|_{\rho=\gamma(p)} \tilde{\gamma}(p) dp,$$

subject to:

- $\gamma(0) = E[|\mathbf{x}|^2] = P$  and  $\gamma(\infty) = 0$
- $\gamma(p)$  is a monotonically non-increasing and non-negative function of  $p$

**WE NEED CLOSED-FORM EXPRESSION FOR SHANNON-TRANSFORM**

# TOTAL MULTICAST RATE

$$\mathbf{R}_p \triangleq \mathbf{A}_p \mathbf{U} \mathbf{B} \mathbf{U}^H \mathbf{A}_p$$

The average rate achievable by the broadcast approach for a user with  $p \in (0,1] \sim W(p)$

$$\frac{1}{N} R = \frac{1}{N} \int_0^\infty w(p) R(p) dp = \int_0^\infty w(p) \int_0^p \frac{\partial}{\partial \rho} \mathcal{V}_{\mathbf{R}_p}(\rho) \Big|_{\rho=\gamma(p)} dp$$

Optimizing  $R$  with respect to  $\gamma(p)$  consists of maximizing

$$\frac{1}{N} R = \int_0^\infty (1 - W(p)) \frac{\partial}{\partial \rho} \mathcal{V}_{\mathbf{R}_p}(\rho) \Big|_{\rho=\gamma(p)} \tilde{\gamma}(p) dp,$$

subject to:

- $\gamma(0) = E[|\mathbf{x}|^2] = P$  and  $\gamma(\infty) = 0$
- $\gamma(p)$  is a monotonically non-increasing and non-negative function of  $p$

$$(1 - W(p)) \frac{\partial}{\partial \rho} \mathcal{V}_{\mathbf{R}_p}(\rho) \Big|_{\rho=\gamma(p)} - w(p) \frac{\partial}{\partial \rho} \mathcal{V}_{\mathbf{R}_p}(\rho) \Big|_{\rho=\gamma(p)} = 0$$

**WE NEED CLOSED-FORM EXPRESSION FOR SHANNON-TRANSFORM**

# BROADCAST APPROACH

$$\mathbf{y}_p = \mathbf{A}_p \mathbf{U} \mathbf{B} \mathbf{x} + \mathbf{z};$$

$$\frac{1}{N} R = \int_0^\infty (1 - W(p)) \left. \frac{\partial}{\partial \rho} \mathcal{V}_{\mathbf{R}_p}(\rho) \right|_{\rho=\gamma(p)} \tilde{\gamma}(p) dp,$$

$$\mathbf{R}_p \triangleq \mathbf{A}_p \mathbf{U} \mathbf{B} \mathbf{U}^H \mathbf{A}_p$$

$$(1 - W(p)) \left. \frac{\partial}{\partial \rho} \mathcal{V}_{\mathbf{R}_p}(\rho) \right|_{\rho=\gamma(p)} - w(p) \left. \frac{\partial}{\partial \rho} \mathcal{V}_{\mathbf{R}_p}(\rho) \right|_{\rho=\gamma(p)} = 0$$

Solving the Euler-Lagrange equation we need expressions:

$$\mathcal{V}_{\mathbf{R}_p}(\rho) \triangleq \lim_{N \rightarrow \infty} \frac{1}{N} \mathbb{E} [\log |\mathbf{I} + \rho \mathbf{R}_p|], \quad \frac{\partial}{\partial \rho} \mathcal{V}_{\mathbf{R}_p}(\rho) = \frac{1}{\rho} (1 - \eta_{\mathbf{R}_p}(\rho))$$



# OBJECTIVE

Evaluate Shannon and  $\eta$ -transform of the following matrix

$$\mathbf{R}_p = \mathbf{A}_p \mathbf{U} \mathbf{B} \mathbf{U}^\dagger \mathbf{A}_p$$

$\mathbf{U}$  Arbitrary Matrix

$\mathbf{A}_p$  N x N diag matrix  $(\mathbf{A}_p)_i \in \{0,1\}$   $P\{(\mathbf{A}_p)_i = 1\} = p$

$\mathbf{B}$  N x N diag matrix  $(\mathbf{B})_i \in \{0,1\}$   $P\{(\mathbf{B})_i = 1\} = q$

Interlude:

# RANDOM MATRIX THEORY

# THE STIELTJES TRANSFORM

The Stieltjes transform (also called the Cauchy transform) of an arbitrary random variable  $X$  is defined as:

$$S_X(z) = \mathbb{E} \left[ \frac{1}{X - z} \right]$$

Inversion formula was obtained by Stieltjes in 1894:

$$f_X(\lambda) = \lim_{\omega \rightarrow 0^+} \frac{1}{\pi} \operatorname{Im} \left[ S_X(\lambda + j\omega) \right]$$

**Rationale for Stieltjes:** Description of Asymptotic Distribution of Singular Values (Marčenko-Pastur (1967))

# THE $\eta$ -TRANSFORM

The  $\eta$ -transform of a nonnegative random variable  $X$  is given by:

$$\eta_X(\rho) \triangleq \mathbb{E} \left[ \frac{1}{1 + \rho X} \right]$$

where  $\rho$  is a nonnegative real number, and thus,  $0 < \eta_X(\rho) \leq 1$

**Rationale for  $\eta$ :** Description of Asymptotic Distribution of Singular Values + Signal Processing Insight

# THE SHANNON TRANSFORM

The Shannon transform of a nonnegative random variable  $X$  is defined as:

$$\mathcal{V}_X(\rho) \triangleq \mathbb{E} [\log (1 + \rho X)] ,$$

where  $\rho$  is a nonnegative real number.



# RELATIONSHIP BETWEEN TRANSFORMS

- Relationship  $\eta$ -Shannon

$$\gamma \frac{d}{d\gamma} \mathcal{V}_X(\gamma) = 1 - \eta_X(\gamma)$$

- Relationship  $\eta$ -Stieltjes

$$\eta_X(\gamma) = \frac{\mathcal{S}_X(-\frac{1}{\gamma})}{\gamma}$$

- Relationship Shannon-Stieltjes

$$\gamma \frac{d}{d\gamma} \mathcal{V}_X(\gamma) = 1 - \frac{1}{\gamma} \mathcal{S}_X\left(-\frac{1}{\gamma}\right)$$

# $\eta$ -TRANSFORM OF A RANDOM MATRIX

Given a  $N \times N$  Hermitian matrix  $\mathbf{R}$ :

The  $\eta$ -transform of its asymptotic ESD is given by

$$\eta_{\mathbf{R}}(\rho) \triangleq \mathbb{E} \left[ \frac{1}{1 + \rho \lambda(\mathbf{R})} \right] = \lim_{N \rightarrow \infty} \frac{1}{N} \mathbb{E} \left[ \text{Tr} (\mathbf{I} + \rho \mathbf{R})^{-1} \right]$$

**$\eta$ -transform of a Random Matrix: Minimum Mean Square Error of the vector channel**

# SHANNON TRANSFORM OF A RANDOM MATRIX

Given a  $N \times N$  Hermitian matrix  $\mathbf{R}$ :

The Shannon transform of its asymptotic ESD is given by

$$\mathcal{V}_{\mathbf{R}}(\rho) \triangleq \mathbb{E} [\log (1 + \rho \lambda(\mathbf{R}))] = \lim_{N \rightarrow \infty} \frac{1}{N} \mathbb{E} [\log |\mathbf{I} + \rho \mathbf{R}|]$$

$$\frac{\partial}{\partial \rho} \mathcal{V}_{\mathbf{R}}(\rho) = \frac{1}{\rho} (1 - \eta_{\mathbf{R}}(\rho)) .$$

Shannon-transform of a Random Matrix: Mutual Information of the N-vector channel

# RANDOM MATRIX THEORY ( $N \rightarrow \infty$ )

$$\mathcal{V}_{\mathbf{R}_p}(\rho) \triangleq \lim_{N \rightarrow \infty} \frac{1}{N} \mathbb{E} [\log |\mathbf{I} + \rho \mathbf{R}_p|], \quad \eta_{\mathbf{R}_p}(\rho) \triangleq \mathbb{E} \left[ \frac{1}{1 + \rho \lambda(\mathbf{R}_p)} \right]$$

$$\frac{\partial}{\partial \rho} \mathcal{V}_{\mathbf{R}_p}(\rho) = \frac{1}{\rho} (1 - \eta_{\mathbf{R}_p}(\rho))$$

ASYMP. RM THEORY: CLOSE-FORM EXPRESSION FOR SHANNON AND  $\eta$ -TRANSFORM

# $\mathbf{R} = \mathbf{H}\mathbf{H}^\dagger$ WITH $\mathbf{H}$ $pN \times qN$ IID MATRIX

- Shannon Transform:

$$\begin{aligned}\mathcal{V}(\gamma) = & \log \left( 1 + \gamma - \frac{1}{4} \mathcal{F}(\gamma, \beta) \right) \\ & + \frac{1}{\beta} \log \left( 1 + \gamma\beta - \frac{1}{4} \mathcal{F}(\gamma, \beta) \right) - \frac{\log e}{4\beta\gamma} \mathcal{F}(\gamma, \beta)\end{aligned}$$

- $\eta$ -Transform:

$$\eta_{\mathbf{R}}(\gamma) = \left( 1 - \frac{\mathcal{F}(\gamma, \beta)}{4\gamma} \right) \quad \beta = \frac{p}{q}$$

$$\mathcal{F}(x, z) = \left( \sqrt{x(1 + \sqrt{z})^2 + 1} - \sqrt{x(1 - \sqrt{z})^2 + 1} \right)^2$$



# OBJECTIVE

Evaluate Shannon and  $\eta$ -transform of the following matrix

$$\mathbf{R}_p = \mathbf{A}_p \mathbf{U} \mathbf{B} \mathbf{U}^\dagger \mathbf{A}_p$$

$\mathbf{U}$  Arbitrary Matrix

$\mathbf{A}_p$  N x N diag matrix  $(\mathbf{A}_p)_i \in \{0,1\}$   $P\{(\mathbf{A}_p)_i = 1\} = p$

$\mathbf{B}$  N x N diag matrix  $(\mathbf{B})_i \in \{0,1\}$   $P\{(\mathbf{B})_i = 1\} = q$

# $\mathbf{R} = \mathbf{H}\mathbf{H}^\dagger$ WITH $\mathbf{H}$ $pN \times qN$ IID MATRIX

- Shannon Transform:

$$\mathcal{V}(\gamma) = \log \left( 1 + \gamma - \frac{1}{4} \mathcal{F}(\gamma, \beta) \right) + \frac{1}{\beta} \log \left( 1 + \gamma\beta - \frac{1}{4} \mathcal{F}(\gamma, \beta) \right) - \frac{\log e}{4\beta\gamma} \mathcal{F}(\gamma, \beta) \quad \beta = \frac{p}{q}$$

$$\mathbf{R}_p = \mathbf{A}_p \mathbf{U} \mathbf{B} \mathbf{U}^\dagger \mathbf{A}_p$$

$\mathbf{U}$   $N \times N$  IID matrix     $\mathbf{A}_p$   $N \times N$  diag matrix     $\mathbf{B}$   $N \times N$  diag matrix

$$(\mathbf{A}_p)_i \in \{0,1\} \quad P\{(\mathbf{A}_p)_i = 1\} = p \quad (\mathbf{B})_i \in \{0,1\} \quad P\{(\mathbf{B})_i = 1\} = q$$

$$\mathbf{R}_p = \mathbf{A}_p \mathbf{U} \mathbf{B} \mathbf{U}^\dagger \mathbf{A}_p \text{ WITH } \mathbf{U} \text{ } N \times N \text{ HAAR MATRIX}$$

- Shannon Transform:

$$\mathcal{V}(\gamma) = q \log(1 + \gamma(1 - \hat{e})) + d(e \parallel \hat{e})$$

$$\hat{e} = \frac{e}{\eta_{\mathbf{R}_p}(\gamma)}$$

- $\eta$ -Transform:

$$\eta_{\mathbf{R}_p}(\gamma) = \frac{2\gamma(p-1)(q-1)}{1 - \gamma(p+q-2) - \sqrt{\mathcal{G}(\gamma, p, q)}}$$

$$\mathcal{G}(z, x, y) = z^2(x - y)^2 + 2z(x + y - 2xy) + 1.$$

$$\mathbf{R}_p = \mathbf{A}_p \mathbf{U} \mathbf{B} \mathbf{U}^\dagger \mathbf{A}_p \text{ WITH } \mathbf{U} \text{ } N \times N \text{ FOURIER MATRIX}$$

**Theorem:**

$\mathbf{U} \mathbf{B} \mathbf{U}^\dagger$  and  $\mathbf{A}_p$  are asymptotically free.

- Shannon Transform:

$$\mathcal{V}(\gamma) = q \log(1 + \gamma(1 - \hat{e})) + d(e \parallel \hat{e})$$

$$\hat{e} = \frac{e}{\eta_{\mathbf{R}_p}(\gamma)}$$

- $\eta$ -Transform:

$$\eta_{\mathbf{R}_p}(\gamma) = \frac{2\gamma(p-1)(q-1)}{1 - \gamma(p+q-2) - \sqrt{\mathcal{G}(\gamma, p, q)}}$$

TULINO, CAIRE, SHAMAI, VERDU, "CAPACITY OF CHANNELS WITH FREQUENCY-SELECTIVE AND TIME-SELECTIVE FADING," IEEE TRANS. INFORMATION THEORY, 2010.

# BACK TO OUR PROBLEM

# SOLVING THE EULER-LAGRANGE EQUATION

$$(1 - W(p)) \left. \frac{\partial}{\partial \rho} \dot{\mathcal{V}}_{\mathbf{R}_p}(\rho) \right|_{\rho=\gamma(p)} - w(p) \left. \frac{\partial}{\partial \rho} \mathcal{V}_{\mathbf{R}_p}(\rho) \right|_{\rho=\gamma(p)} = 0$$

We need expressions for the mutual information and its derivatives, for the channel model:

$$\mathbf{y}_p = \mathbf{A}_p \mathbf{U} \mathbf{B} \mathbf{x} + \mathbf{z},$$

$$\mathcal{V}_{\mathbf{R}_p}(\rho) \triangleq \lim_{N \rightarrow \infty} \frac{1}{N} \mathbb{E} [\log |\mathbf{I} + \rho \mathbf{R}_p|], \quad \frac{\partial}{\partial \rho} \mathcal{V}_{\mathbf{R}_p}(\rho) = \frac{1}{\rho} (1 - \eta_{\mathbf{R}_p}(\rho))$$

# CHANGE OF VARIABLE

We can rewrite the Euler-Lagrange equation in terms of the eta-transform and its derivative with respect to p:

$$-(1 - W(p)) \frac{\dot{\eta}_{\mathbf{R}_p}(\gamma(p))}{\gamma(p)} - \frac{w(p)}{\gamma(p)} (1 - \eta_{\mathbf{R}_p}(\gamma(p))) = 0$$

With a change of variable  $\gamma = \gamma(p)$ , we can re-write the rate:

$$R = \int_0^1 (W(p) - 1) \left. \frac{\partial}{\partial \rho} \mathcal{V}_{\mathbf{R}_p}(\rho) \right|_{\rho=\gamma(p)} \dot{\gamma}(p) dp$$

as:

$$R = \int_{\gamma(\mathcal{A})} (1 - W(g(\gamma))) \frac{1 - \eta_{\mathbf{R}_{g(\gamma)}}(\gamma)}{\gamma} d\gamma.$$

# RANDOM MATRIX THEORY ( $N \rightarrow \infty$ )

$$-(1 - W(p)) \frac{\dot{\eta}_{\mathbf{R}_p}(\gamma(p))}{\gamma(p)} - \frac{w(p)}{\gamma(p)} (1 - \eta_{\mathbf{R}_p}(\gamma(p))) = 0$$

U IID

$$\eta_{\mathbf{R}_p}(\gamma) = 1 - \frac{\mathcal{F}(\gamma p, \frac{q}{p})}{4\gamma},$$

$$\mathcal{F}(x, z) = \left( \sqrt{1 + x(1 + \sqrt{z})^2} - \sqrt{1 + x(1 - \sqrt{z})^2} \right)^2$$

U HAAR / FOURIER

$$\eta_{\mathbf{R}_p}(\gamma) = \frac{2\gamma(p-1)(q-1)}{1 - \gamma(p+q-2) - \sqrt{\mathcal{G}(\gamma, p, q)}}$$

$$\mathcal{G}(z, x, y) = z^2(x-y)^2 + 2z(x+y-2xy) + 1.$$

ASYMP. RM THEORY: CLOSE-FORM EXPRESSION FOR SHANNON AND  $\eta$ -TRANSFORM



# FINDING THE RIGHT SOLUTION

- Having expressions for both  $\eta_{\mathbf{R}_p}(\gamma)$  and  $\dot{\eta}_{\mathbf{R}_p}(\gamma)$ , we can replace them into the Euler-Lagrange and solve for  $\gamma(p)$  for all values of  $p \in [0, 1]$ .
- **Such solution must be discussed carefully.** In general,  $\gamma(p)$  is equal to the constant  $P$  (total power) for some interval  $[0, p_0]$  and it is equal to the constant 0 for some interval  $[p_1, 1]$  with  $p_0 \leq p_1$ .
- In the range  $[p_0, p_1]$ ,  $\gamma(p) = \hat{\gamma}(p)$  where the latter is a monotonically non-increasing function of  $p$ .
- In order to find  $p_0$  and  $p_1$  we replace the boundary conditions  $\gamma = P$  and  $\gamma = 0$  into the Euler-Lagrange equation and solve for  $p$ . Hence, we verify that in the interval  $[p_0, p_1]$  the solution is indeed unique and monotonic.

# U: AN IID RANDOM MATRIX

Fix:

$$P = 10, \quad q = 0.2, \quad w(p) = \begin{cases} 1 & 0 \leq p \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

Then:

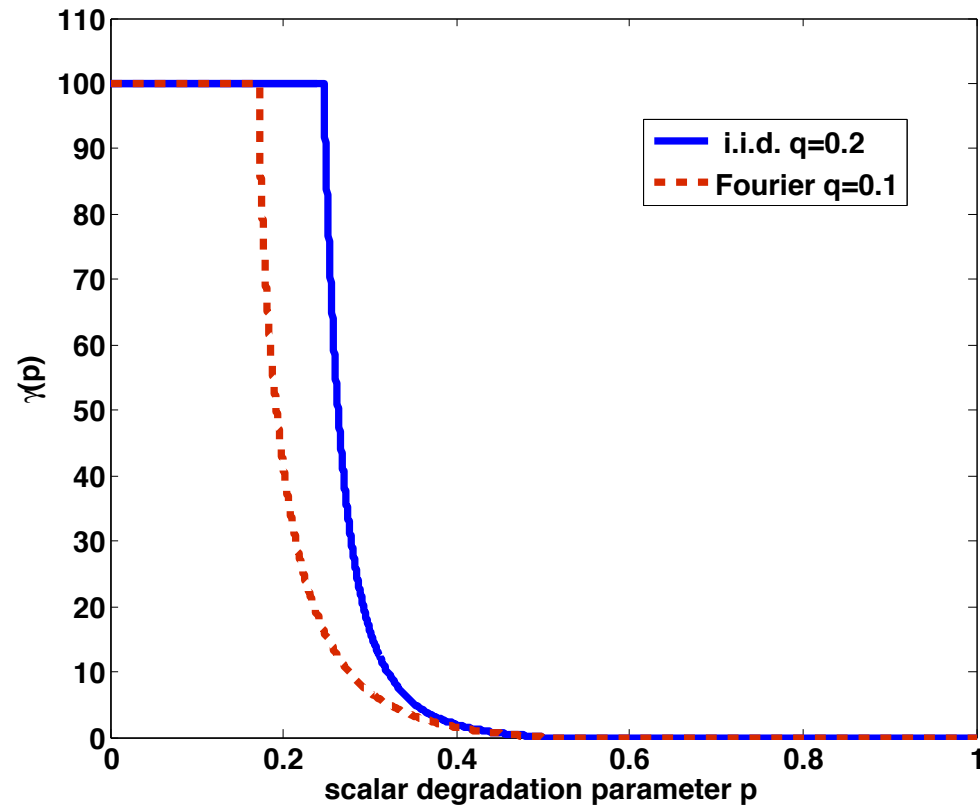
$$\gamma(p) = \begin{cases} P & 0 \leq p \leq 0.32 \\ \hat{\gamma}(p) & 0.32 \leq p \leq 0.5 \\ 0 & 0.5 \leq p \leq 1 \end{cases}$$

$p_0$   
 $p_1$

where  $\hat{\gamma}(p)$  is the solution for  $p \in [0.32, 0.5]$   $\xrightarrow{\gamma \rightarrow 0} q(1 - 2p) = 0,$

$$\frac{1-p}{2\gamma} \left[ 1 - \frac{1 + \gamma(p-q)}{\sqrt{1 + 2\gamma(p+q) + \gamma^2(p-q)^2}} \right] - \frac{\mathcal{F}(\gamma p, \frac{q}{p})}{4\gamma^2} = 0.$$

# $\gamma(p)$ FOR $\mathbb{U}$ IID AND HAAR MATRIX



# CONCLUSIONS

- MIMO (linear Gaussian) channel where:

- Inputs turned on and off at random,
- Outputs sampled at random

- Given:

- input sparsity probability,
- statistics of the MIMO channel
- broadcast approach as coding technique

method for calculating the power allocation across the layers, in order to maximize the system weighted sum rate for arbitrary non-negative weighting function .

- Analytical solutions both for iid and Haar distributed MIMO channel matrices are provided.

- The Haar case accounts also for DFT matrices, with application to sparse spectrum signals with random sub-Nyquist sampling.

..... Bell Labs 