

Lecture 18 IC and Conclusion June 4, 2024

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Announcements & Agenda

- Announcements
 - Final is Friday at 2pm, get email from Helen helen.niu@stanford.edu
 - Due Saturday at 3pm.
 - Course evaluation link is open at eval
 - Solutions go up early tomorrow morning (Wed).
- Agenda
 - CIC Optimization (from Thursday)
 - LIC Design
 - Research & Machine-Learning/AI Challenges (optional)



CIC Optimization

CIC's "Optimum" Spectrum Balancing (no GDFEs)

- OSB minimizes weighted energy sum for given b_{min}.
 - There is no crosstalk cancellation

$$\min_{\{R_{\boldsymbol{x}\boldsymbol{x}}(u,n)\}} \qquad \sum_{u=1}^{U} w_u \cdot \mathcal{E}_u \\ ST: \qquad \text{for } u = 1, ..., U \\ 0 \le \sum_n \text{trace} \{R_{\boldsymbol{x}\boldsymbol{x}}(u,n)\} \le \mathcal{E}_{u,max} \ .$$

• OSB relates **b** to $R_{xx}(u, n)$ by:

$$b_{u} = \sum_{n} \log_{2} \frac{\mid H_{uu,n} \cdot R_{\boldsymbol{x}\boldsymbol{x}}(u,n) \cdot H_{uu,n}^{*} + \mathcal{R}_{noise}(u,n) \mid}{\mid \mathcal{R}_{noise}(u,n) \mid}$$

- $\mathcal{R}_{noise}(u,n) = I + \sum_{i \neq u} \widetilde{H}_{u,i,n} \cdot R_{xx}(i,n) \cdot \widetilde{H}_{u,i,n}^*$
 - All other users are crosstalk-noise additions.
- Tonal Lagrangian for minPOSB
 - Minimize each individually, and sum.
 - It's not convex (no sequential-differences' transformation).
 - The *w* is determined as an output of optimization.
 - Optimization can also maximize negative for the maxROSB.

 $L_n(R_{oldsymbol{xx}}(u,n),oldsymbol{b}_n,oldsymbol{w},oldsymbol{ heta}) = \sum_{u=1}^U w_u \cdot \mathcal{E}_{u,n} - heta_u \cdot b_{u,n}$



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L17:4

Still has minimum, "integer programming"

•
$$SNR(u,n) = \frac{|\widetilde{H}_{u,u,n} \cdot R_{xx}(u,n) \cdot \widetilde{H}_{u,u,n}|}{|R_{noise}(u,n)|}$$

$$b_u = \sum_n \log_2 \left(1 + \frac{\mathrm{SNR}(u, n)}{\Gamma} \right)$$

 Partition energy range or use discrete integer bit quanta for scalar case:

$$M = rac{\max_u \boldsymbol{\mathcal{E}}(u)}{\Delta \mathcal{E}}$$
 or $b = 0, 1, ..., bitcap$

- These are integer-programming part.
- Energy or bit step: For each tone, search M^U possible energies (or $2^{U \cdot bitcap}$ bit quanta) to minimize tonal Lagrangian and add these tonals.
 - The users' energies are weighted, and the weights are optimized (compute $\mathcal L$ update to make small),
 - to ensure that the energy constraint is met.
 - Or equivalently the θ is similarly adjusted if w is given.
- Constraint: External to energy-bit step, Use a descent method to update the *θ* or *w* Lagrange multiplier for rate constraints:

$$\mathcal{L} = \sum_{u=1}^{U} \sum_{n=0}^{\overline{N}-1} w_u \cdot \mathcal{E}_{u,n} - \theta_u \cdot b_{u,n}$$

$$w = w + \epsilon \cdot \Delta \mathcal{E} \text{ or}$$

$$w_u \leftarrow \frac{w_u}{2} \text{ if } < \mathcal{E}_{u,max}$$

$$w_u \leftarrow 2 \cdot w_u \text{ if } > \mathcal{E}_{u,max}$$

w update is for admissibility.

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OSB.m (this maximizes weighted rate-sum)

function [S1, S2, b1, b2] = osb(Hmag_sq, No, E, theta, mask, ...
gap, bitcap, cb)

osb and also finds w1 energy weight for USER 1 A. Chowdhery ~2010 ; Updated by J. Cioffi in 2024. It presently handles only 2 users, so U=2.

Inputs

Hmag sq is a N \times 2 \times 2 where N is FFT size. N inferred from this. is a 1 x U white-noise power spectra density matrix. No If Hmag_sq is complex BB, then No should be the one-sided PSD. is a 1 x U energy vector. F theta is a 1 x U user-rate weighting vector. mask is an N x U PSD maximum allowed. is the (non-dB) linear gap (so 1 if 0 dB gap). gap bitcap is a 1 x U maximum number of bits allowed per tone. is 2 for real baseband and 1 for cplex bband cb Outputs **Subroutines** is user 1's Nx1 PSD S1 adjust w 52 is user 2's Nx1 PSD Values. b1 is user 1's Nx1 bit distribution h2 is user 2's Nx1 bit distribution calls optimize l2.m, which calls optimize s.m User order is reversed with respect to class convention.

```
>> H2=zeros(1,2,2);
H2(:..,1) = [0.6400 0.2500]; % note this is squared mag each term
H_2(:,:,2) = [0.4900 \ 0.3600];
>> Noise = 1.0e-04 * [ 1.0000 1.0000];
>> Ex = [1 1];
>> mask = [ 1 1];
>> gap = 1;
>> bitcap = [ 15 15];
>> [S1, S2, b1, b2] = osb(H2, Noise, Ex, [0.5.5], mask, gap, bitcap, 2)
S1 = 0.6398
S2 = 0
b1 = 6% note < 6.3 for the GDFE based IC's maximum L11:16
b_2 = 0
>> [S1, S2, b1, b2] = osb(H2, Noise, Ex, [0.01.99], mask, gap, bitcap, 2)
S1 = 0
S2 = 0.1419
b1 = 0
b2 = 4.5000 < 5.9 for L11:16
```

L17:6

• The OSB search can be very complex for U > 3.



Multitone OSB Example



- L18 later compares this to IW (like SWF, Except for IC – see last section today).
- We could similar have a minPOSB,
- Or even admOSB.

Searching for more Software on OSB and related.

GDFE's cancellation of crosstalk makes a large difference.



CIC Optimization allow multiple-user decoding

PS7.5 (5.20) Simple CIC Design

minPIC = more "optimum"

- minPIC concept allows for each receiver u to cancel $i \in \mathcal{D}_u(\Pi, p_{xy}, b)$; the decodable set.
- Order has been restored 🐸
- The optimization is
 - (i, u) = (RCVR, USER).



- θ still has U terms, and they determine the U! "sensible" orders Π.
- The achievable-region constraint remains convex already (like minPMAC).
- Each receiver may use a GDFE, but precoders are not possible (on IC).



3-User Order example

• Given a θ , say for example with $\theta_3 > \theta_1 > \theta_2$, they determine all receivers' order:



Do same for other 2 receivers

RCVR 1 optimization of rate sum

$$A \stackrel{\Delta}{=} |H_{1,3}|^2 \cdot (\mathcal{E}_{2,3} + \mathcal{E}_{3,3}) + |H_{1,2}|^2 \cdot (\mathcal{E}_{1,2} + \mathcal{E}_{2,2}) + I$$

- $B \stackrel{\Delta}{=} |H_{1,3}|^2 \cdot \mathcal{E}_{1,3} + A$
- $C \stackrel{\Delta}{=} |H_{1,1}|^2 \cdot \mathcal{E}_1 + B$
- $D \stackrel{\Delta}{=} |H_{1,2}|^2 \cdot \mathcal{E}_{1,2} + C$

RCVR 2 optimization of rate sum

$$A \stackrel{\Delta}{=} |H_{2,3}|^2 \cdot (\mathcal{E}_{1,3} + \mathcal{E}_{3,3}) + |H_{2,1}|^2 \cdot (\mathcal{E}_{1,1} + \mathcal{E}_{3,1}) + I$$

$$B \stackrel{\Delta}{=} |H_{2,3}|^2 \cdot \mathcal{E}_{2,3} + A$$

$$C \stackrel{\Delta}{=} |H_{2,1}|^2 \cdot \mathcal{E}_{2,1} + B$$

$$D \stackrel{\Delta}{=} |H_{1,1}|^2 \cdot \mathcal{E}_2 + C$$

$$b_{2,3} = \log_2(B) - \log_2(A)$$

$$b_{2,1} = \log_2(C) - \log_2(B)$$

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$$b_{1,3} = \log_2(B) - \log_2(A)$$

$$b_1 = \log_2(C) - \log_2(B)$$

$$b_{1,2} = \log_2(D) - \log_2(C) .$$

$$b_{2,3} = \log_2(B) - \log_2(A)$$

$$b_{2,1} = \log_2(C) - \log_2(B)$$

$$b_2 = \log_2(D) - \log_2(C) .$$

$$(3 - 1)$$

$$\sum_{u=1}^{3} \theta_{u} \cdot b_{u} \bigg\}_{RCVR1opt} = (\theta_{3} - \theta_{1}) \cdot \log_{2}(B) + (\theta_{1} - \theta_{2}) \cdot \log_{2}(C) + \theta_{2} \cdot \log_{2}(D) \qquad \bigg\{\sum_{u=1}^{3} \theta_{u} \cdot b_{u}\bigg\}_{RCVR2opt} = (\theta_{3} - \theta_{1}) \cdot \log_{2}(B) + (\theta_{1} - \theta_{2}) \cdot \log_{2}(C) + \theta_{2} \cdot \log_{2}(D)$$

- Six energies repeat select from each such energy pair, that which has corresponding lowest rate/info.
- Outer $\boldsymbol{\theta}$ loop (e.g., Ellipsoid) remains the same as minPMAC.



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Generalize – first order them to simplify

Create order of users for each of (reordered) users

$ heta_U$		$ heta_u$		$ heta_1$
$\boldsymbol{U^2} \setminus \{(1:U,U),(U,1:U-1)\}$		$\boldsymbol{U^2} \setminus \{(1:U,u),(u,1:U-1)\}$	• • •	$\boldsymbol{U^2} \setminus \{(U,1:U), (1,1:U-1)\}$
(U,U)		(u,U)	•••	1,U-1
				:
		(u, U-u+1)		(1,1)
(1,U)		(U,u)	•••	(U,1)
(U,U-1)		÷	•••	÷
÷		$egin{array}{c} (1,u)\ (u,U-u-1) \end{array}$	•••	÷
÷				÷
(U,1)		(u,1)	•••	(U,U)

Table 5.2: Generalized of overall decoding order pairs given descending-order θ .



Generalize A,B,C, D

$$\begin{cases} K_{1,u} \qquad \stackrel{\Delta}{=} \sum_{i \neq u} H_{u,i} \cdot \left(\sum_{j \neq i} R_{\boldsymbol{x}\boldsymbol{x}}(i,j) \right) \cdot H_{u,i}^{*} + I \qquad \text{for } b_{u,U} \\ K_{2,u} \qquad \stackrel{\Delta}{=} H_{u}(2) \cdot R_{\boldsymbol{x}\boldsymbol{x}}(u, 2U - 3, 2) \cdot H_{u}^{*}(2^{nd}) + K_{1,u} \qquad \text{for } b_{u,U-1} \\ \vdots \qquad \vdots \\ K_{u,u} \qquad \stackrel{\Delta}{=} H_{u,2U-u+1}(2) \cdot R_{\boldsymbol{x}\boldsymbol{x}}(u, 2U - u + 1(2^{nd})) \cdot H_{u,2U-u+1}^{*}(2) + K_{u-1,u} \quad \text{for } b_{u} \\ \vdots \qquad \vdots \\ K_{2U-2,u} \qquad \stackrel{\Delta}{=} H_{u,1}(2) \cdot R_{\boldsymbol{x}\boldsymbol{x}}(u, 1(2^{nd})) \cdot H_{u,1}^{*}(2) + K_{2U-3,u} \qquad \text{for } b_{u,1} \end{cases}$$

- This is convex in those quantities optimized
- Need the outer subgradient loop on theta to drive IC rate vector to bmin.

Software awaits writing.



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LIC Design

Iterative WF borrows MAC's SWF for the IC





IW Illustrated for the LIC



Repeat until converged



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Wireless Potential Use (Resource Blocks)





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L18:17

Near-Far Example

Downlink has another transmitter for another IC user closer (the "near" user).



Uplink has another transmitter for another IC user closer (the "near" user).





Example IC with IWF (near-far)



 $\begin{bmatrix} y_{1A} \\ y_{1B} \end{bmatrix} = .5 \cdot \begin{bmatrix} x_{1A} \\ x_{1B} \end{bmatrix} + .9 \cdot \begin{bmatrix} x_{2A} \\ x_{2B} \end{bmatrix} + \begin{bmatrix} n_{1A} \\ n_{1B} \end{bmatrix}$ $\begin{bmatrix} y_{2A} \\ y_{2B} \end{bmatrix} = \begin{bmatrix} x_{2A} \\ x_{2B} \end{bmatrix} + \begin{bmatrix} .9 & .1 \end{bmatrix} \cdot \begin{bmatrix} x_{1A} \\ x_{1B} \end{bmatrix} + \begin{bmatrix} n_{1A} \\ n_{1B} \end{bmatrix}$

 $\sigma_1^2 = \sigma_2^2 = 0.1$ (noises independent)

Energy 1A = 2.0	Energy 2B = 2.0

- Which receiver has near-far issue?
 - RCVR 1 in both bands
- Who is near user?
 - User 2



Tabular Tracking of IW

- User 2 reacts to user 1 crosstalk.
- User 1 then counter acts.
- Further reduction of energy on user 2 band B.
- IW here converges in 2 cycles and
 - solution looks like FDM.
- This is better than equal energy on both users in both bands.



Table 2 – Simple IW Example						
	Band A	Band B				
User 1	$\mathcal{E}_{1A} = 1$	$\mathcal{E}_{1B} = 1$				
User 2	$\frac{1}{g_{2A}} = .1 + (.9)^2 = .91$	$\frac{1}{g_{2B}} = .1 + (.1)^2 = .11$				
	$\boldsymbol{\mathcal{E}}_{2A} + .91 = \boldsymbol{\mathcal{E}}_{2B} + .11$					
	$\mathcal{E}_{2A} + \mathcal{E}_{2B} = 2$					
	$\mathcal{E}_{2A} = .6$	$\mathcal{E}_{2B} = 1.4$				
User 1	$\frac{1}{g_{1,1}} = \frac{.1 + .6 \cdot (.9)^2}{(.5)^2} = 2.344$	$\frac{1}{g_{s,p}} = \frac{.1 + 1.4 \cdot (.9)^2}{(.5)^2} = 4.936$				
	(.5)	$-\epsilon + 4.036$				
	$\mathcal{E}_{1A} + 2.344 = \mathcal{E}_{1B} + 4.936$					
	$\mathcal{E}_{1A} + \mathcal{E}_{1B} = 2$					
	$\mathcal{E}_{1A} = 2$	$\mathcal{E}_{2B}=0$				
User 2	$\frac{1}{g_{2A}} = .1 + 2 \cdot (.9)^2 = 1.72$	$\frac{1}{g_{2B}} = .1 + 0 \cdot (.1)^2 = .1$				
	$\mathcal{E}_{2A} + 1.72 = \mathcal{E}_{2B} + .1$					
	$\mathcal{E}_{2A} + \mathcal{E}_{2B} = 2$					
	${\cal E}_{_{2A}} = .19$	$\mathcal{E}_{2B} = 1.81$				
User 1	Remains $\mathcal{E}_{1A} = 2$ $\mathcal{E}_{2B} = 0 \rightarrow IW$ has	s converged $\frac{1}{g_{1,4}} = \frac{.1+.19\cdot.81}{.25} = 1.0156$				
Data rates	$\log_2(1+2/1.0156) = 1.5701$	0				
User 1						
Total User 1	1.6 bits					
Data rates User 2	$\log_2(1+.19/1.72) = .15$	$\log_2(1+1.81/.1) = 4.26$				
Total User 2	4.4	·				
Rate Sum	6.0 bits					

IW_polite.m (integer bits like osb.m)

<pre>% function [b, E] = iw_polite(N, df, U, Hmag, No, Ex, mask, gap, mode, b_target, bitcap,cb) %</pre>
% Calculates data rates of M users and corresponding bit distributions and
% using iterative waterfilling
%
% Inputs
% N: number of sub-channels
% M: number of users
% Hmag: squared channel transfer and crosstalk matrix (N x U x U matrix)
* Hmag(h,1,j) is the crosstalk transfer function from loop 1 to j at the nth bin.
% No: noise energy/sample
% Ex: signal energy/SYMBOL
\approx mask: PSD mask - largest value N X U \approx gap: gap (not in dB)
% mode: (U x 1 vector) each value is one of the followings
% 0 - rate adaptive
% 1 – fixed margin (power minimization) % 2 – margin adaptive
% b_target: target bits on 1 DMT symbol for modes 1 and 2
<pre>% bitcap: maximum possible number of bits at each frequency bin</pre>
% CD =1 TOR CPLX BB and =2 TOR REAL BB
% Outputs
8
% b: bit distribution (N x U matrix) % F: energy distribution (N x II matrix)
8
% Remarks
<pre>% Iterate waterfiling for each user 10 times % Youngize(Sean) Kim = modified 1 Cioffi April 2024</pre>
······································

- Sum is same, user 1 is better in osb.
- With continuous bit distribution, osb would be slightly better.

>> [b, E] = iw_polite(8, 2, H3.*conj(H3), Noise, [8 8], mask, gap, zeros(8.1), [5 5], bitcap,1)				
b =				
0 8.0000	>> [b1 b2] %(osb)			
0 8.0000	0 8			
2.0264 1.0000	0 8			
8.0000 0	7 0			
8.0000 0	8 0			
8.0000 0	0 0			
2.0264 1.0000	8 0			
0 8.0000	7 0			
	0 8			
E =	>> [S1 S2] = %(osb)			
0 0.6375	0 0.6375			
0 0.7469	0 0.7469			
0.6300 0.3609	0.7017 0			
0.8272 0	0.8272 0			
0.7064 0	0 0			
0.8272 0	0.8272 0			
0.6300 0.3609	0.7017 0			
0 0.7469	0 0.7469			
>> sum(b) = 28.0529 26.0000				
\sim Sum(D) = 28.0529 20.0000				

Energies < 8 because iw calls campello.m, which allows only integer bits (like osb.m).



IW.m (non-integer) – not in text, but at website

	> [h E] - iw(9.2 U2 *coni(U2) Noice [9.9] gas	$a_{1} = \frac{1}{2} \left(\frac{1}{2} \right) \left[\frac{1}{2} \right] \left[\frac{1}{2} \left[\frac{1}{2} \right] \left[\frac{1}{2} \left[\frac{1}{2} \right] \left[\frac{1}{2} \left[\frac{1}$
<pre>function function [b, E] = iw(N, U, Hmag, No, Ex, gap, mode, b_target,cb)</pre>	$\sim [0, c] - w(o, z, no. conj(no), worse, [o o], ga$	5, 20105(0,1), [5 5],1)
Calculates data rates of M users and corresponding bit distributions and	b =	
Energy distributions	0 9.5897	>> [b1 b2] %(osb)
using iterative water ritering.	0 9.3612	0 8
Inputs	1.4972 1.4479	0 8
N: number of sub-channels	9.2050 0	7 0
U: number of users	9.4329 0	8 0
Hmag: squared channel transfer and crosstalk matrix (N x U x U matrix) Hmag(n,i,i) is the crosstalk transfer function from loop i to i	9.2050 0	0 0
at the nth bin.	1.4972 1.4479	8 0
No: noise power spectrum per tone (N x U)	0 9.3612	7 0
mask: PSD mask – largest value N x U	E=	0 8
gap: gap in dB	0 1.9238	
0 - rate adaptive	0 1.9233	>> [S1 S2] = %(osb)
1 - fixed margin (power minimization)	1.1329 1.1148	0 0.6375
2 – margin adaptive b target: target bits on 1 DMT symbol for modes 1 and 2	1.9112 0	0 0.7469
bitcap: maximum possible number of bits at each frequency bin	1.9118 0	0.7017 0
cb =1 for cplx BB and =2 for real BB	1.9112 0	0.8272 0
Outputs	1.1329 1.1148	0 0
	0 1.9233	0.8272 0
E: energy distribution (N x U matrix)		0.7017 0
Demonths	>> sum(b) % = 30.8374 31.2079 (62>54!!)	0 0.7469
Remarks Iterate waterfiling for each user 10 times	>>sum(E) % = 8 8	
Youngjae(Sean) Kim – modified J. Cioffi, April 2024		

Energies = 8 now with fractional bits



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More sophisticated situation (IC of MAC & BC)

- 25 bi-directional users (so really 50 users if they all share same band each echo cancels itself only.)
 - Otherwise, there is no GDFE xtalk cancellation in this simulation, only IW.
- Turn on MA WF for them all and let them run versus fixed spectrum with (PAM) b = 6 bits/Hz,
 - which was state of art prior to IW





Multi-Level Water-fill Illustration



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Near-Far Example



- Near-Far can arise with RIS (reflective intelligent surfaces) for adjacent bands of RIS.
- Near-Far can occur in wireline also "remote terminals" or "distribution units."
- Adjacent cells in cellular (or Wi-Fi).



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Achievable Region Comparison

- IW better than fixed, but not so good
- This plots 25 users with ML IW and with C
 - See upper right
 - Blue curves allow for margin on ML IW.
- ML IW is pretty close to OSB.

Working to locate better IW and ML-IW, OSB.







End Lecture 18 & EE 379- 2024

THANK YOU !!

ML & Challenges

Nesting

Use minPmac/bc on node channels



- Use ML Water-Fill between nodes
- Efficient Algorithms?
 - How/where to update?



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AI ("machine learned") Approximations?



- Each of these "boxes" (subnetworks) can be intense calculation
- The overall recursive cycling is actually then more intense



Machine learned "minPxx"

- minPMAC (and minPIC) optimize, but may have long run-times and numerical issues
 - They accept channel+noise and data rates (and maybe energy in admxx)



Extended to nesting, complex networks



Where, and from what, to compute precoders?



Algorithms (ML/AI) based on digital twin of this to update precoders?



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O-RAN/Xhaul split 7.2 (over) simplified





Correlate Design choices with User Reaction

Thumbs down
Exit score
(2) (2) (2) (2) (2)

Calls to IT/ISP



Group success rate



 Repair/Intervention counts

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Diagnostics & Analytics Learn the reward function V **employee feedback and link data**



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Optimize QoE (value)

Optimization (management) Objective is to improve service to "green"

- Use analytics to derive
 - Priorities (orders, weights)
- Optimize accordingly





A Network State Machine: Reinforcement Learning



- Network user/link may be in a state or profile
 - Some are ok (user happy or green) ; amber on the edge ;
 - Red very likely unhappy
- Markov (state-machine) models
- Learn the profile, apply appropriate design for each state
 - Objective is move to green state with profile change

$$P_a = \begin{bmatrix} p_{3/3} & p_{3/2} & 0 & 0\\ 0 & 0 & p_{2/1} & 0\\ 0 & p_{1/2} & 0 & p_{1/0}\\ p_{0/3} & 0 & 0 & p_{0/0} \end{bmatrix}$$

 $\pi = P_a \cdot \pi$ Markov (stationary) distribution



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A Network State Machine: Reinforcement Learning

- Determines Next Action (State)
 - Profile $\{R_{xx}(u), b_u, [G_u \ W_u]\}$, u = 1, ..., U'
- GYR
 - Try to get to better states
 - But this depends on cost of doing so
- Markov (state-machine) models



Can include, MCS, number of spatial streams, channel, spectrum, priority (weights $[w \ \theta]$), etc



Estimating the probabilities and States

- Better on-line/real-time "fading" distributions
- While all the "Raleigh, Ricean, log-normal, angle-spread, delay-spread " models create simulation environments that range through many situations, they're not specific to situation
- Each channel/user may need to estimate probability distributions for "fading/xtalk"
 - How do do this well
 - Ergodic state machines (Markov models) or slowing varying
 - Digital Twins?
 - Know the settings for each in advance?
- Then identify which state and associated pre-computed design?
 - Would this save a lot of computing energy?
- Are Pe and data-rates the right measures? \rightarrow Quality of Experience (QoE)
 - Learned from user "feedback" dor +
- Reinforcement Learning? (Recurrent Neural Net as base?)



Reflective Intelligent Surfaces (RIS)



- The RIS matrix Q_H satisfies $||Q_H||_F^2 \leq G_H$, the RIS gain it may also satisfy
 - *Q_H* is unitary matrix (preserves energy)
 - Q_H is diagonal, and usually also unitary, to be phase/gain-only adjustment on each antenna port (in-to-out)
 - *Q_H* has individual elements restricted
- For a given $R_{m{x}m{x}}$, maximize over Q_H $\mathcal{I}(m{y};m{x}) = \log_2 |R_{n,RIS} + H_{RIS} \cdot R_{m{x}m{x}} \cdot H_{RIS}^*|$
- For a given Q_H, maximize the same over R_{xx}

$$R_{\boldsymbol{n}\boldsymbol{n},RIS} = \left[egin{array}{cc} R_{\boldsymbol{n}\boldsymbol{n}} & 0 \ 0 & R_{\boldsymbol{n}\boldsymbol{n},out} + Q_H \cdot R_{\boldsymbol{n}\boldsymbol{n}in} \cdot Q_H^* \end{array}
ight]$$

Iterate

Sec 2.11.4 Ju

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