

***In-situ* Physical Adjoint Computing in Multiple-Scattering Electromagnetic Environments for Wave Control**

John Guillamon, Chengzhen Wang, Zin Lin, Tsampikos Kottos

Acknowledgement: Prof. Steven Johnson, (Simons Presentation 2023)

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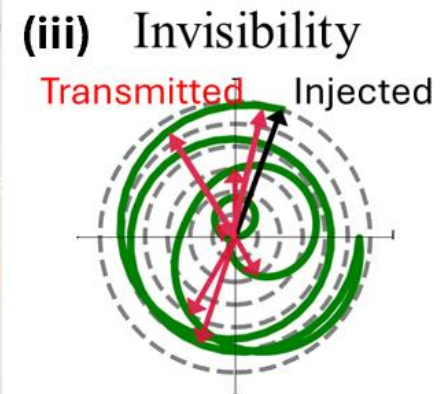
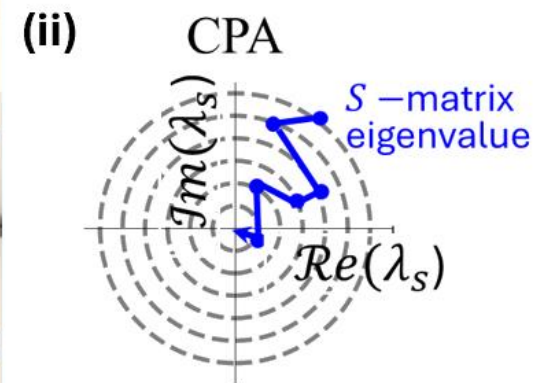
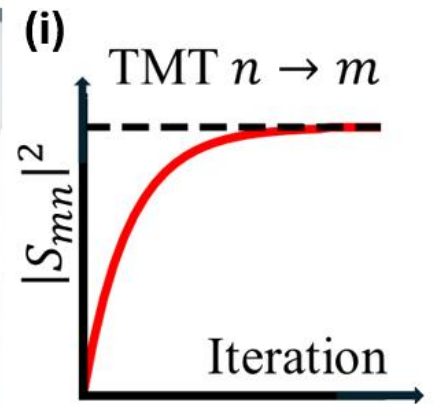
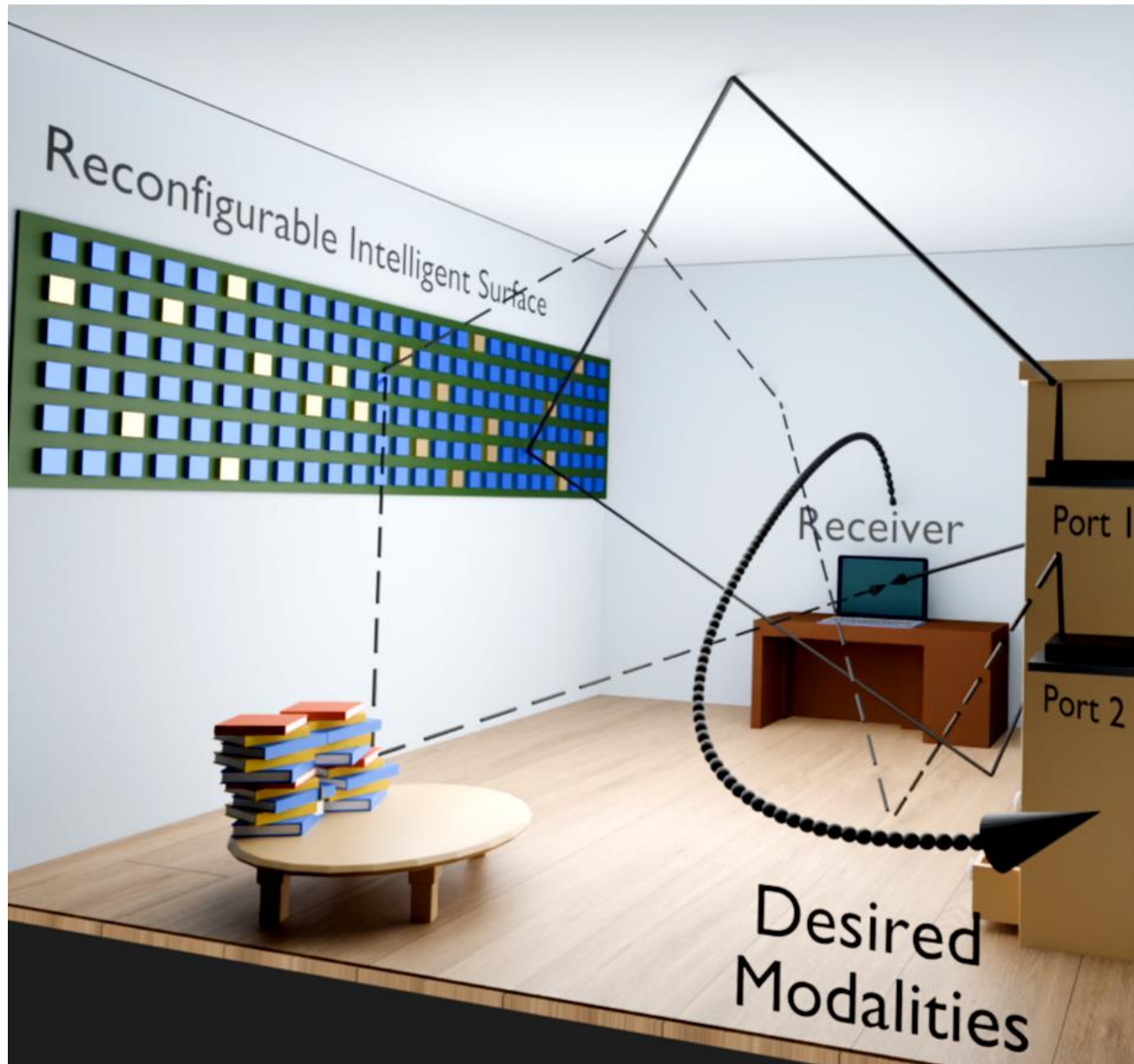


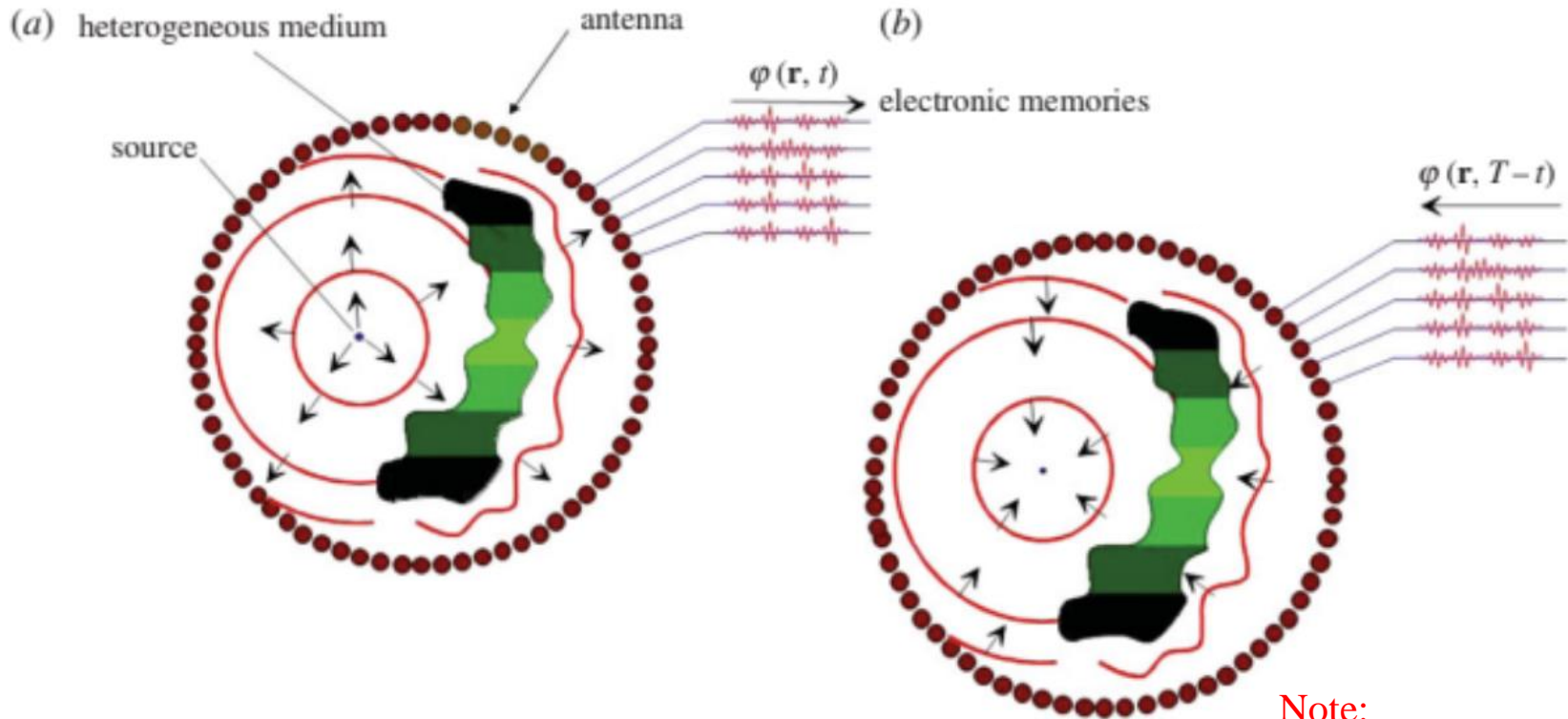


- General Problem: Challenges in Wireless Communications
- Methodologies
 1. Time-Reversal Mirror Protocol
 2. Linear and Nonlinear Wavefront Shaping Protocols
 3. Cavity Shaping Protocols
- In-Situ Adjoint Method
 1. General Principles of Adjoint Method
 2. Physical Implementation in Complex Networks
- In-Situ Modality Examples
 1. Targeted Mode Transmission
 2. Coherent Perfect Absorption
 3. Invisibility
- In-Silico Generalization
- Outlook



Challenges in Wireless Communications





Time-Reversal Mirrors (TRM) in 4 steps:

- (i) Target (source) emits a signal
- (ii) Receivers (TRM) register the signal
- (iii) TRM time-reverse the register signal
- (iv) Send back the time-reverse signal

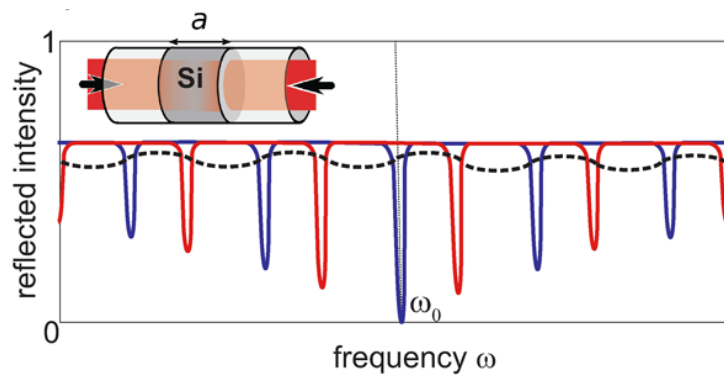
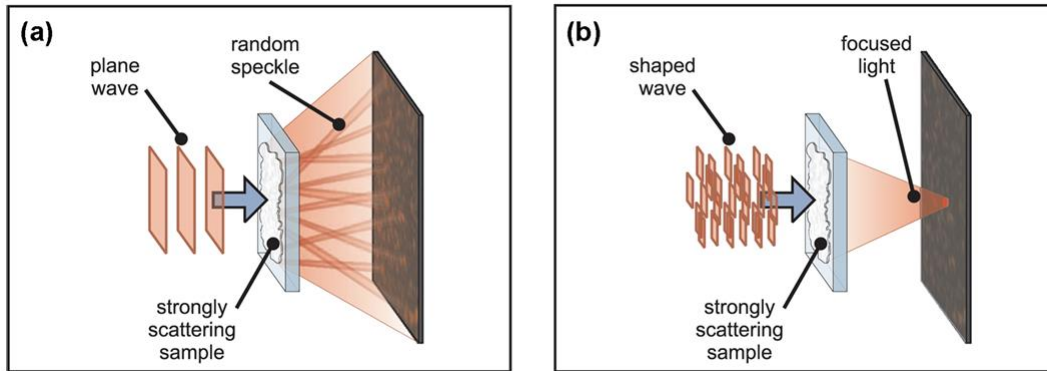
Note:

- 1) The "environment" needs to be "static"
- 2) An exact TR process requires TR of source (from source to sink)

Fink, M. (2016). From Loschmidt daemons to time-reversed waves. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 374



Linear and Nonlinear Wavefront Shaping Protocols



$$|\mathcal{O}\rangle = \hat{S}(k, \boldsymbol{\gamma})|\mathcal{J}\rangle$$

$$= \lambda(k, \boldsymbol{\gamma})|\mathcal{J}\rangle = 0$$

CPA Condition:

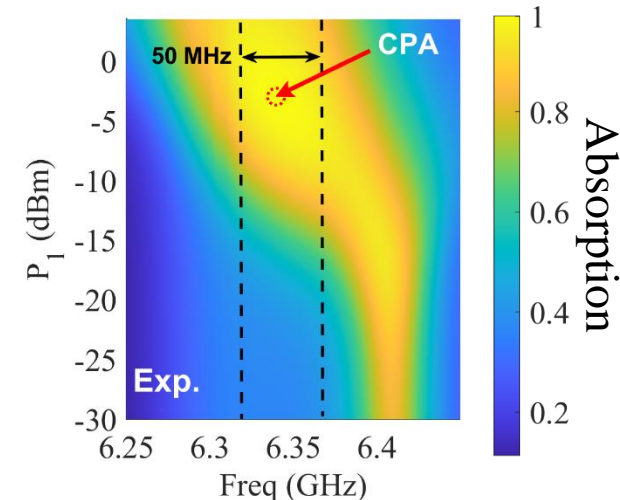
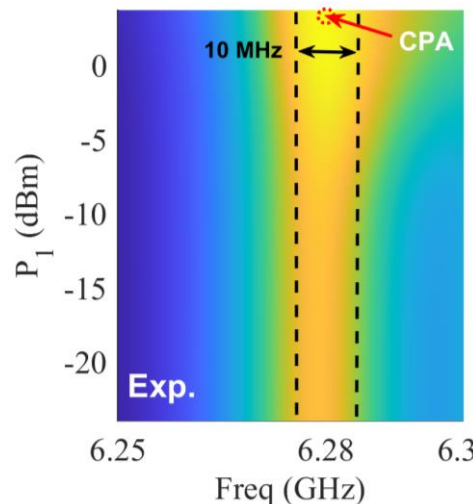
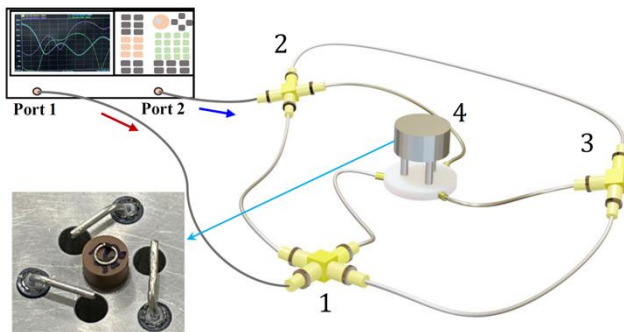
$$\lambda_{CPA}(k_{CPA} \in \mathcal{R}, \boldsymbol{\gamma}_{CPA}) = 0$$

$$|\mathcal{J}\rangle = |\mathcal{J}_{CPA}\rangle$$

Vellekoop, I. M., & Mosk, A. P. (2007). Focusing coherent light through opaque strongly scattering media. *Optics letters*,

Chong, Y. D. Stone A.D., et al. 2010, "Coherent perfect absorbers: time-reversed lasers."

Nonlinear Wavefront Shaping

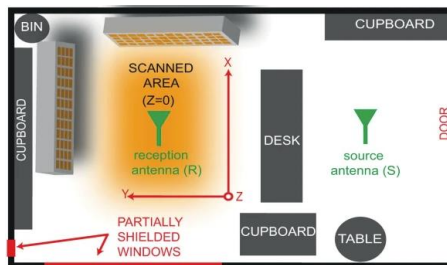
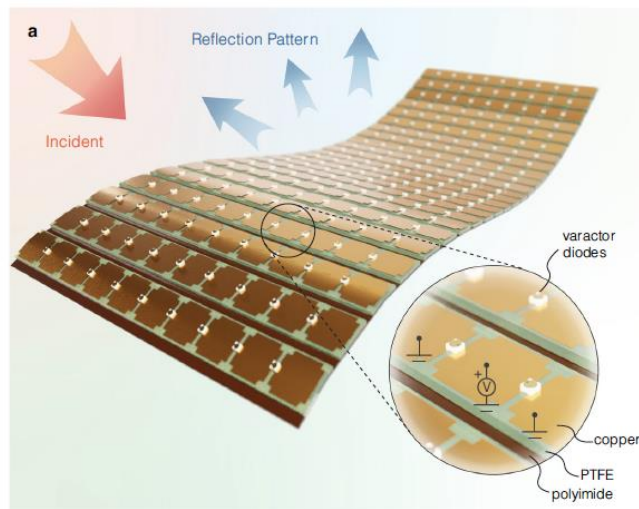
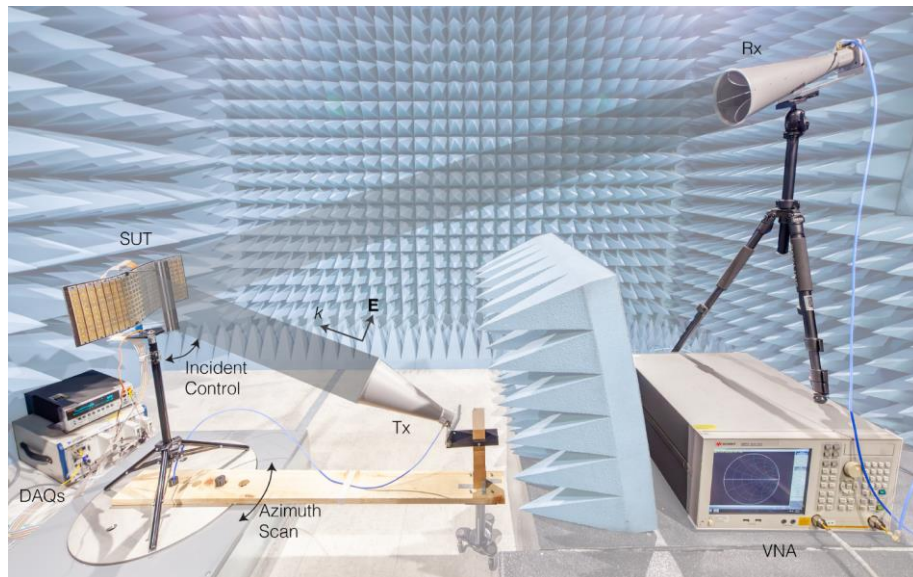


Wang, CZ, Guillaumon, J. Tuxbury, W. et al. "Nonlinearity-induced scattering zero degeneracies for spectral management of coherent perfect absorption in complex systems." *Physical Review Applied* 22.6 (2024): 064093.



Cavity Shaping Protocols

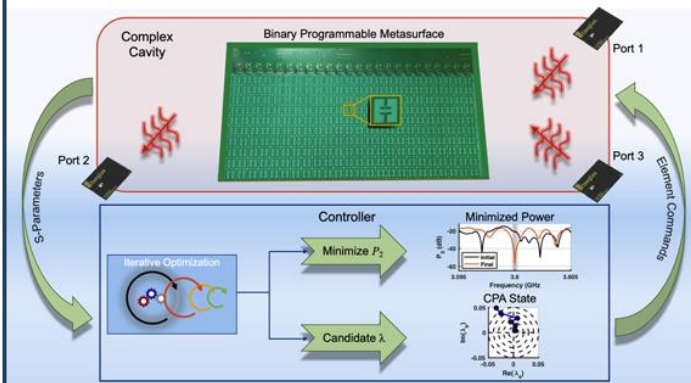
Intelligent Wave Control in Complex Environment



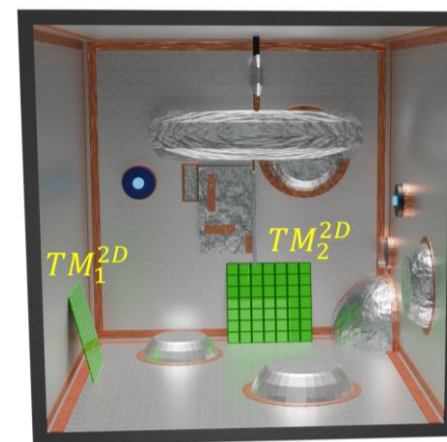
Kaina, N., Dupré, M., Lerosey, G., & Fink, M. (2014). Shaping complex microwave fields in reverberating media with binary tunable metasurfaces. *Scientific reports*, 4(1), 6693.

Wen, Erda, Xiaozhen Yang, and Daniel F. Sievenpiper. "Real-data-driven real-time reconfigurable microwave reflective surface." *Nature Communications* 14.1 (2023): 7736.

Chaotic cavity/Meta-surface

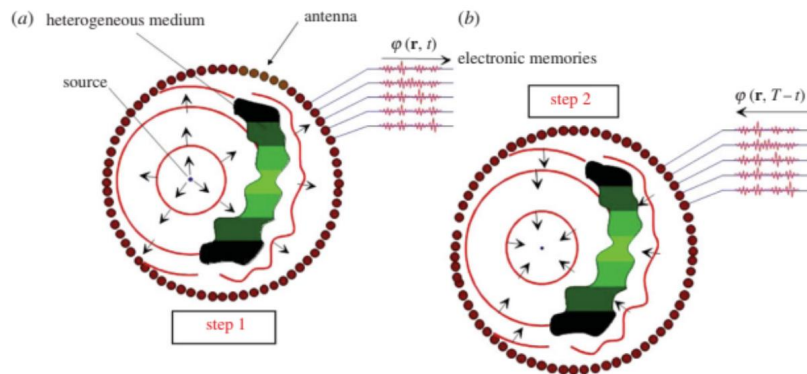


Frazier, B. W., Antonsen Jr, T. M., Anlage, S. M., & Ott, E. (2020). Wavefront shaping with a tunable metasurface: Creating cold spots and coherent perfect absorption at arbitrary frequencies. *Physical Review Research*, 2(4), 043422.

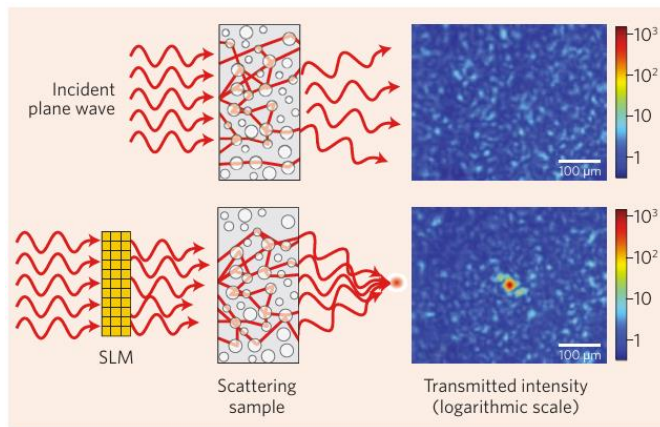


Erb, J., Shaibe, N., Calvo, R., Lathrop, D., Antonsen, T., Kottos, T., & Anlage, S. M. (2024). Novel Topology and Manipulation of Scattering Singularities in Complex non-Hermitian Systems. *arXiv preprint arXiv:2411.01069*.

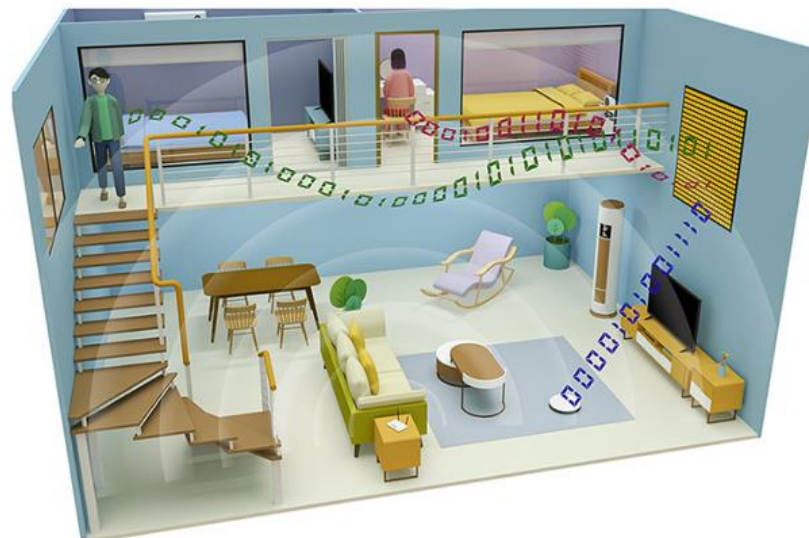
Time Reversal



Wavefront Shaping



Cavity Shaping



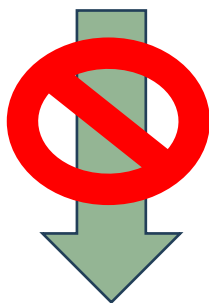


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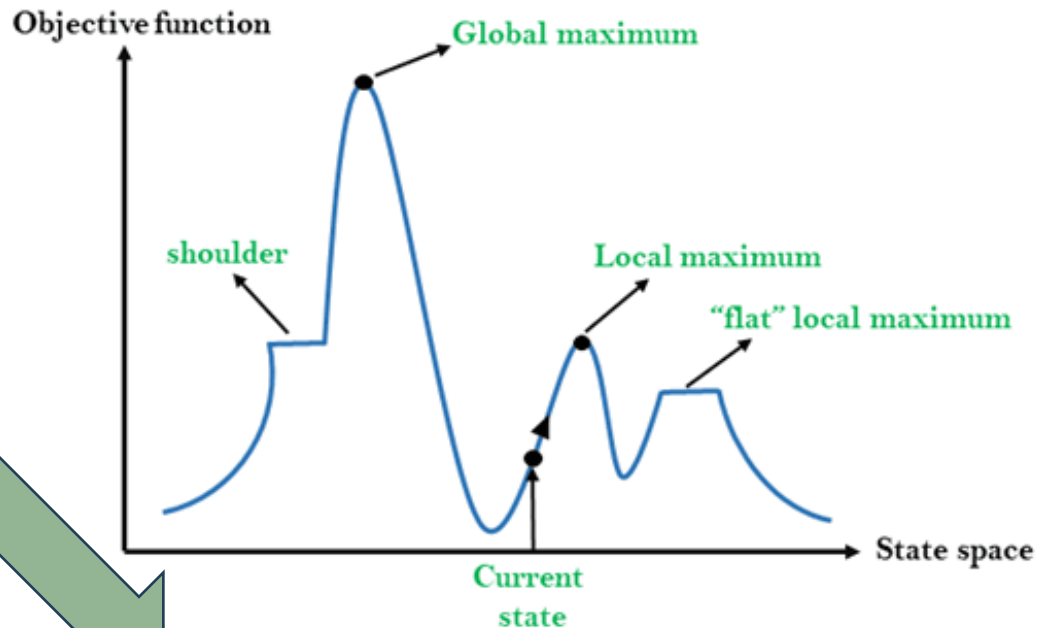


Adjoint-Based Gradient Optimization

Optimization



Gradient-Free:
Bayesian
Surrogate



Gradient-Based:
Finite Difference
Adjoint Method

We propose and demonstrate the use of
an *in-situ* (Experimentally Driven)
Adjoint Method

$g(\mathbf{p}, \Phi, \Phi^*)$: Objective

\mathbf{p} : Parameter Vector

$\mathbf{b}(\mathbf{p})$: Source

$\mathcal{M}(\mathbf{p})$: Wave System

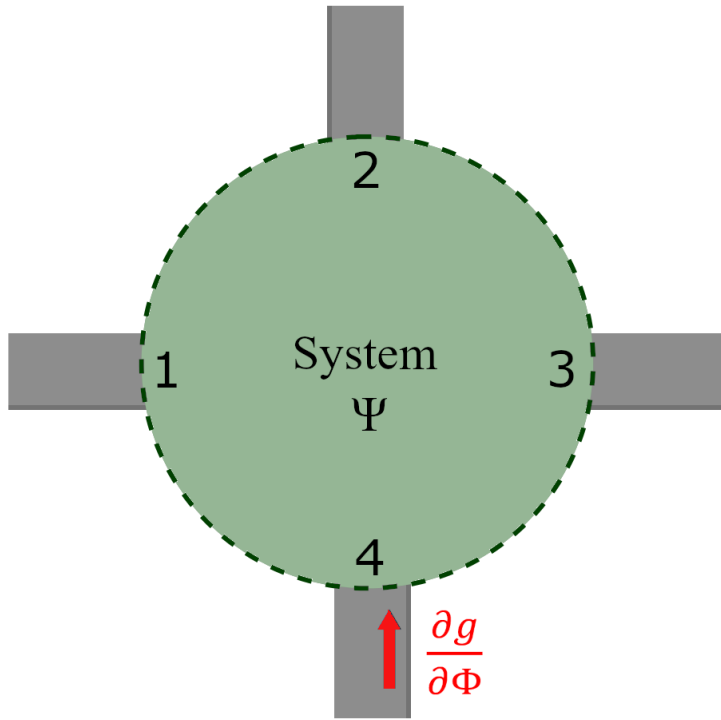
$\Phi(\mathbf{p})$: Forward Field

$\lambda(\mathbf{p})$: Adjoint Field

Forward Problem: $\mathcal{M}(\mathbf{p})\Phi = \mathbf{b}(\mathbf{p})$

Adjoint Problem: $\mathcal{M}^T \lambda = \frac{\partial g}{\partial \Phi}$

Gradient: $\frac{dg}{d\mathbf{p}} = \frac{\partial g}{\partial \mathbf{p}} + \lambda^T \left(\frac{\partial \mathbf{b}}{\partial \mathbf{p}} - \frac{\partial \mathcal{M}}{\partial \mathbf{p}} \Phi \right)$



- Exploit reciprocity: Only one additional “adjoint” measurement needed
- In-situ measurements self-calibrate against real-world losses/detuning
- Real-time, gradient-based optimization without big data sets or neural training neural networks

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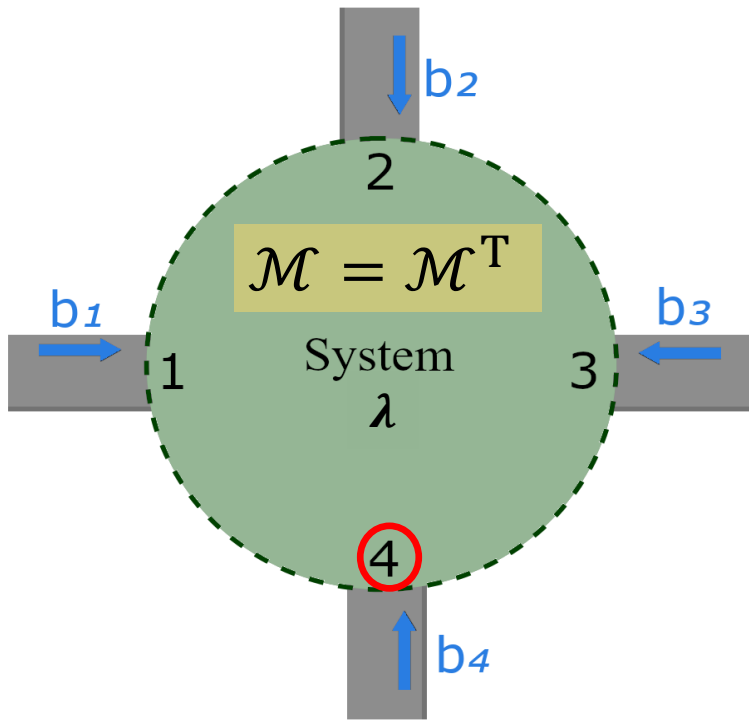
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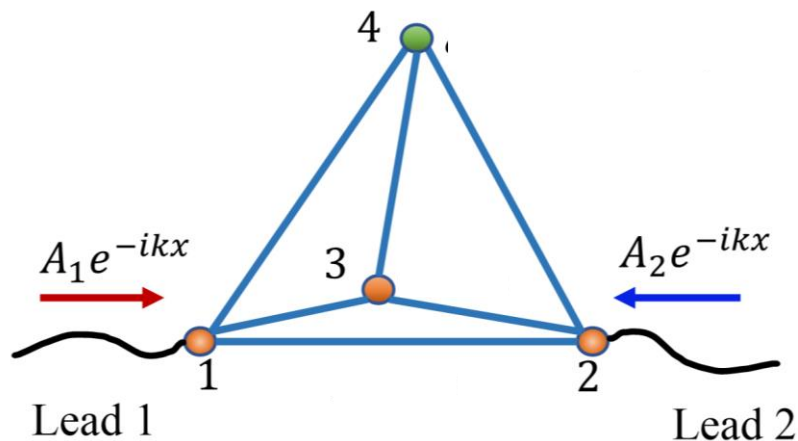
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- Exploit reciprocity: Only one additional “adjoint” measurement needed
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Microwave Graph Network



- Wave equation on each bond:

$$\frac{d^2}{dx_{mn}^2} \psi_{mn}^{(\alpha)} + k^2 \psi_{mn}^{(\alpha)} = 0$$

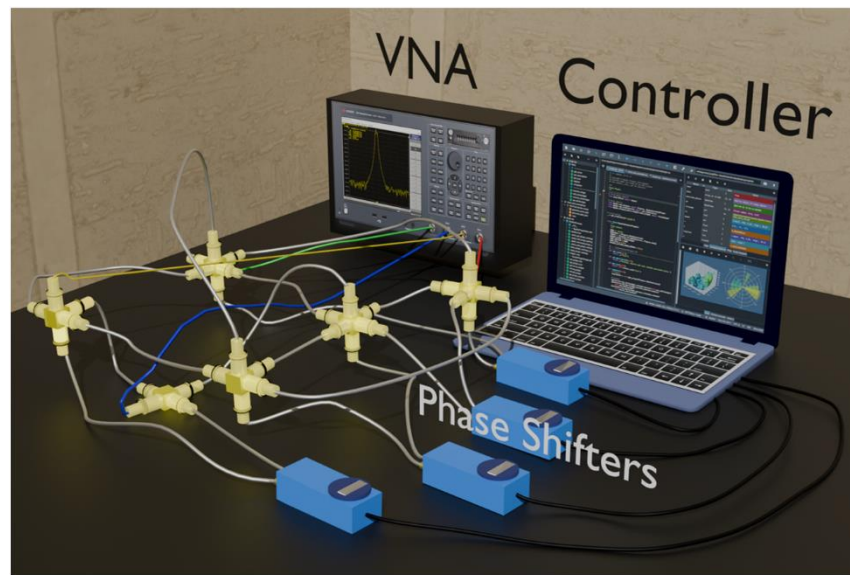
- Wave continuity on each vertex:

$$\psi_{mn}^{(\alpha)}(x_{mn} = 0) = \phi_m^{(\alpha)}$$

$$\psi_{nm}^{(\alpha)}(x_{nm}) = \phi_n^{(\alpha)} \frac{\sin k(L_{nm} - x_{nm})}{\sin kL_{nm}} + \phi_m^{(\alpha)} \frac{\sin kx_{nm}}{\sin kL_{nm}}$$

- Current conservation:

$$\sum_n \left. \frac{d\psi_{mn}^{(\alpha)}}{dx_{mn}} \right|_{x_{mn}=0} + \sum_{\mu=1,2} \delta_{\mu,\alpha} \left. \frac{d\psi_{\mu}^{(\alpha)}}{dx} \right|_{x=0} = 0$$



- Matrix equation for the wave on the vertices

$$(M + iW^T W) \Phi^{(\alpha)} = 2iW^T I^{(\alpha)}$$

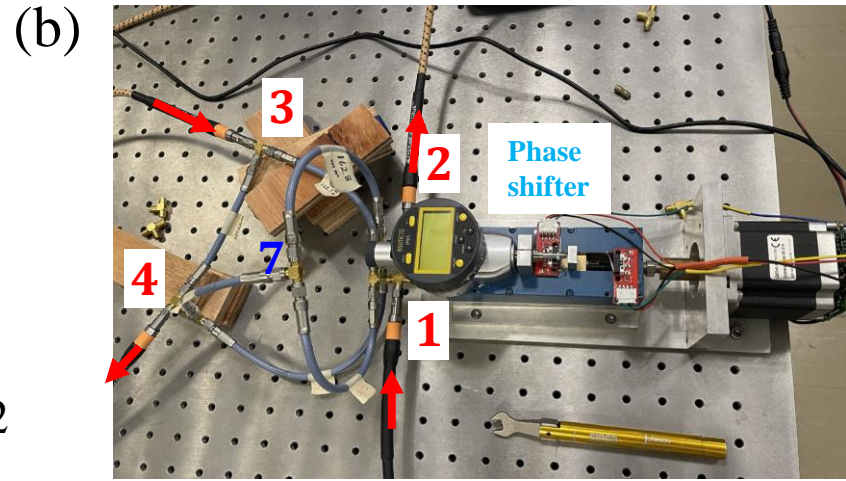
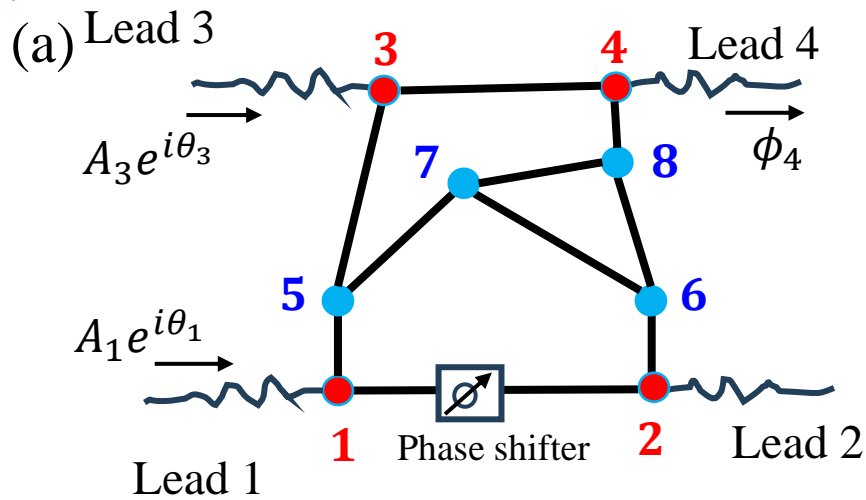
$$M_{mn} = \begin{cases} -\sum_{\gamma \neq m} \mathcal{A}_{m\gamma} \cot kL_{m\gamma}, & m = n \\ \mathcal{A}_{mn} \csc kL_{mn}, & m \neq n \end{cases}$$

$$W = \begin{pmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \end{pmatrix}$$

$$I_n^{(\alpha)} = A_\alpha \cdot \delta_{\alpha,n}$$

T. Kottos and U. Smilansky, PRL, (1997)
 O. Hul et al., Phys. Rev. E 69, 056205 (2004)
 B. Dietz et al., Phys. Rev. E 95, 052202 (2017)

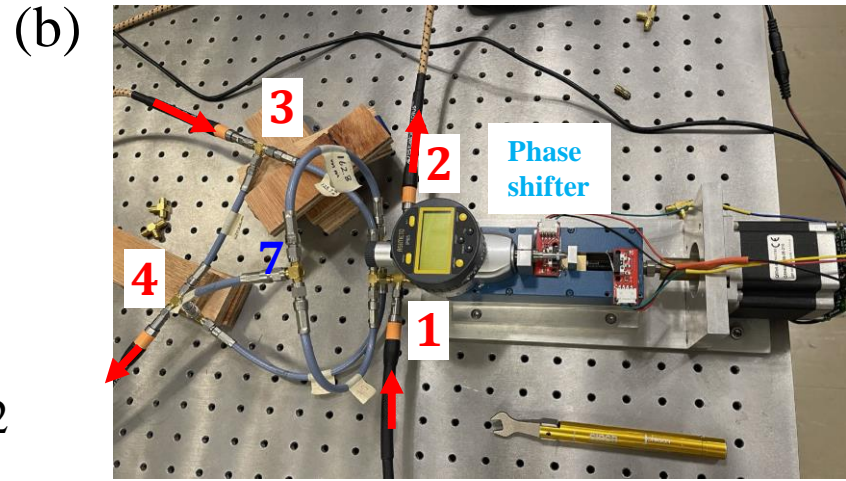
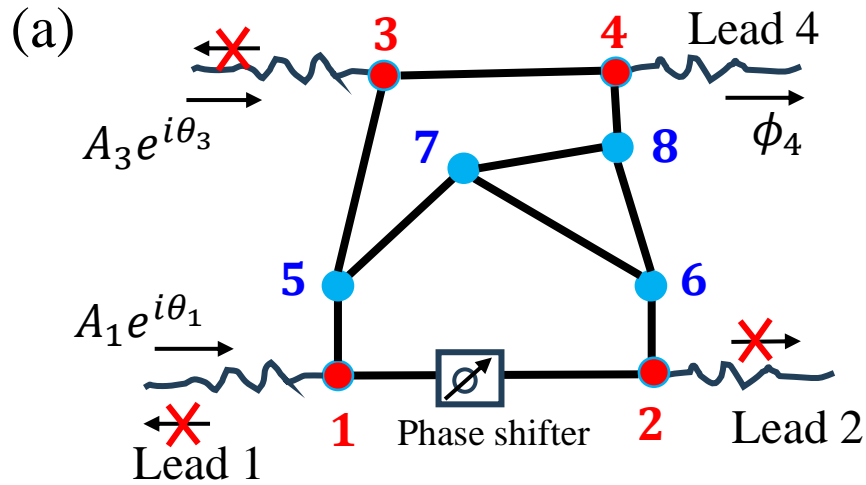
Example Modality 1- Targeted Mode Transport



- Wave input from lead 1 and lead 3. Maximize transmittance at targeted port 4, i.e., maximize the objective function: $g = \frac{|\phi_4|^2}{A_1^2 + A_3^2} = \frac{\phi_4 \phi_4^*}{A_1^2 + A_3^2}$, where ϕ_4 is the wave on vertex 4
- Three control parameters $\mathbf{p} = [L_{12}, A_3, \theta_3]$: length L_{12} tuned by phase shifter, input wave amplitude A_3 and phase θ_3 .
- Gradient based optimization requires knowledge of $\frac{dg}{d\mathbf{p}} = \left[\frac{dg}{dL_{12}}, \frac{dg}{dA_3}, \frac{dg}{d\theta_3} \right]$.



Gradient Measurement: Adjoint Method and Finite Difference Method



- Digital Twin: calculate the gradient, based on modeling (**CPU costly/model inaccurate**).
- Finite difference method requires derivatives for each of the M parameters x at x_0 : $\frac{\partial g}{\partial x} \Big|_{x=x_0} = \frac{g(x_0+\delta) - g(x_0-\delta)}{2\delta}$, i.e., $2M$ measurements and $3M$ operations (**time costly/noise sensitive**)

Our goal is

- (1) Get the gradient/derivative by *in-situ measurement* instead of solving the system equations;
- (2) Minimize the number of measurements/operations (**fast/noise resilient**).



Implementation of Adjoint Method

Optimize the objective function: $g(\mathbf{p}, \Phi(\mathbf{p}), \Phi^*(\mathbf{p})) = \frac{|\phi_4|^2}{A_1^2 + A_3^2} = \frac{\phi_4 \phi_4^*}{A_1^2 + A_3^2}$

$$\frac{dg}{d\mathbf{p}} = \frac{\partial g}{\partial \mathbf{p}} + \frac{\partial g}{\partial \Phi} \frac{\partial \Phi}{\partial \mathbf{p}} + \frac{\partial g}{\partial \Phi^*} \frac{\partial \Phi^*}{\partial \mathbf{p}} = \frac{\partial g}{\partial \mathbf{p}} + \begin{bmatrix} \frac{\partial g}{\partial \Phi} & \frac{\partial g}{\partial \Phi^*} \end{bmatrix} \begin{bmatrix} \frac{\partial \Phi}{\partial \mathbf{p}} \\ \frac{\partial \Phi^*}{\partial \mathbf{p}} \end{bmatrix} \leftarrow ?$$

- The system wave equation:

$$(M + iW^T W)\Phi = 2iW^T I_{in} \quad M_{mn} = \begin{cases} -\sum_{\gamma \neq m} \mathcal{A}_{m\gamma} \cot kL_{m\gamma} + \lambda_m k, & m = n \\ \mathcal{A}_{mn} \csc kL_{mn}, & m \neq n \end{cases}$$

or written as: $f = (M + iW^T W)\Phi - 2iW^T I_{in} = 0$

And the conjugate system equation: $f^* = (M^* - iW^T W)\Phi^* + 2iW^T I_{in}^* = 0$

- Evaluation of $\frac{\partial \Phi}{\partial \mathbf{p}}$ and $\frac{\partial \Phi^*}{\partial \mathbf{p}}$ requires solution of two coupled algebraic equations

$$\frac{df}{d\mathbf{p}} = \frac{\partial f}{\partial \mathbf{p}} + \frac{\partial f}{\partial \Phi} \frac{\partial \Phi}{\partial \mathbf{p}} + \frac{\partial f}{\partial \Phi^*} \frac{\partial \Phi^*}{\partial \mathbf{p}} = 0$$

$$\frac{df^*}{d\mathbf{p}} = \frac{\partial f^*}{\partial \mathbf{p}} + \frac{\partial f^*}{\partial \Phi} \frac{\partial \Phi}{\partial \mathbf{p}} + \frac{\partial f^*}{\partial \Phi^*} \frac{\partial \Phi^*}{\partial \mathbf{p}} = 0$$

Known

$$\begin{pmatrix} \frac{\partial \Phi}{\partial \mathbf{p}} \\ \frac{\partial \Phi^*}{\partial \mathbf{p}} \end{pmatrix} = - \begin{pmatrix} \frac{\partial f}{\partial \Phi} & \frac{\partial f}{\partial \Phi^*} \\ \frac{\partial f^*}{\partial \Phi} & \frac{\partial f^*}{\partial \Phi^*} \end{pmatrix}^{-1} \begin{pmatrix} \frac{\partial f}{\partial \mathbf{p}} \\ \frac{\partial f^*}{\partial \mathbf{p}} \end{pmatrix}$$



Implementation of Adjoint Method

$$\frac{dg}{d\mathbf{p}} = \frac{\partial g}{\partial \mathbf{p}} + \begin{bmatrix} \frac{\partial g}{\partial \Phi} & \frac{\partial g}{\partial \Phi^*} \end{bmatrix} \begin{bmatrix} \frac{\partial \Phi}{\partial \mathbf{p}} \\ \frac{\partial \Phi^*}{\partial \mathbf{p}} \end{bmatrix} = \frac{\partial g}{\partial \mathbf{p}} - \underbrace{\begin{bmatrix} \frac{\partial g}{\partial \Phi} & \frac{\partial g}{\partial \Phi^*} \end{bmatrix}}_{(1 \times 2N)} \underbrace{\begin{pmatrix} \frac{\partial f}{\partial \Phi} & \frac{\partial f}{\partial \Phi^*} \\ \frac{\partial f^*}{\partial \Phi} & \frac{\partial f^*}{\partial \Phi^*} \end{pmatrix}^{-1}}_{(2N \times 2N)} \underbrace{\begin{pmatrix} \frac{\partial f}{\partial \mathbf{p}} \\ \frac{\partial f^*}{\partial \mathbf{p}} \end{pmatrix}}_{(2N \times M)}$$

$$= \lambda^T = (\lambda_1, \lambda_1^*)^T$$

What is the physical meaning of λ ?

$$\begin{pmatrix} M + iW^T W & 0 \\ \begin{pmatrix} \frac{\partial f}{\partial \Phi} \\ \frac{\partial f^*}{\partial \Phi} \end{pmatrix}^T & \begin{pmatrix} \frac{\partial f}{\partial \Phi^*} \\ \frac{\partial f^*}{\partial \Phi^*} \end{pmatrix}^T \end{pmatrix} \begin{pmatrix} \lambda_1 \\ \lambda_1^* \end{pmatrix} = \begin{pmatrix} 0 & 2iW^T I_{adj} \\ \begin{pmatrix} \frac{\partial f}{\partial \Phi} \\ \frac{\partial f^*}{\partial \Phi} \end{pmatrix}^T & \begin{pmatrix} -\frac{\partial g}{\partial \Phi} \\ -\frac{\partial g}{\partial \Phi^*} \end{pmatrix}^T \end{pmatrix}$$

λ_1 is the solution of the Maxwell's Equation for a certain excitation I_{adj} :

$$I_{adj} = \begin{bmatrix} 0, & 0, & 0, & \frac{i}{2} \frac{\phi_4^*}{A_1^2 + A_3^2} \end{bmatrix}$$

Reminder: $f = (M + iW^T W)\Phi - 2iW^T I_{in}$



Implementation of *in situ* Adjoint Method

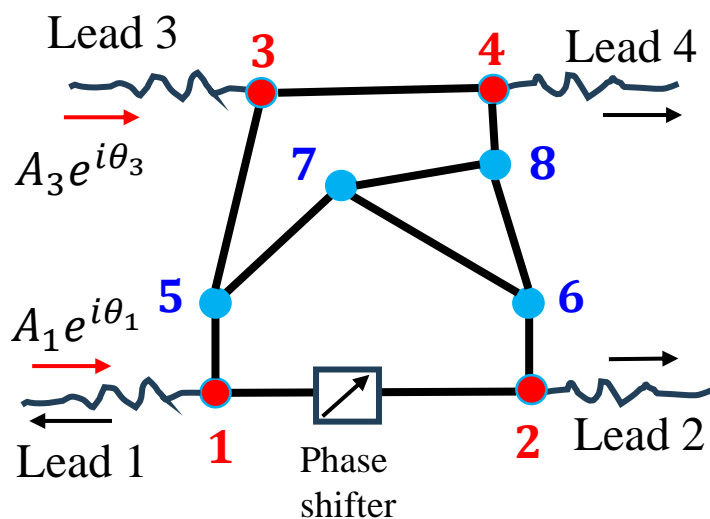
- Forward Equation: ← The same for time-reversal invariance systems → Adjoint (backward) Equation:

$$(M + iW^T W)\Phi = 2iW^T I_{\text{in}}$$

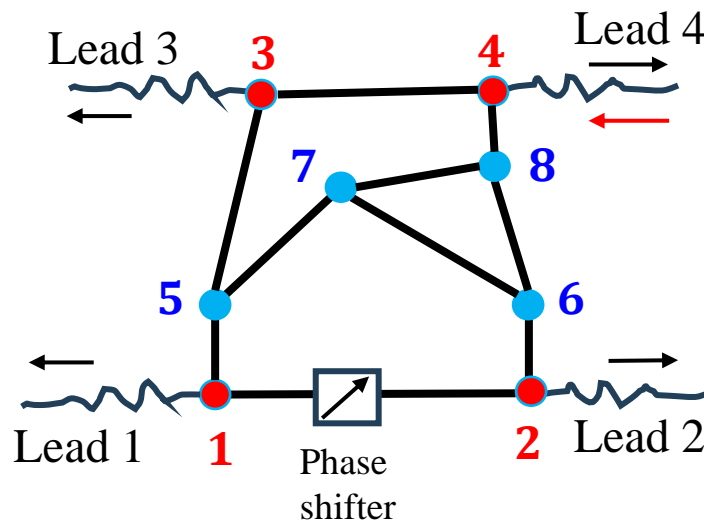
$$(M + iW^T W)\lambda_1 = 2iW^T I_{\text{adj}}$$

$$I_{\text{in}} = [A_1 e^{i\theta_1}, 0, A_3 e^{i\theta_3}, 0]$$

$$I_{\text{adj}} = \left[0, 0, 0, \frac{i}{2} \frac{\phi_4^*}{A_1^2 + A_3^2} \right]$$



Forward



Backward

Instead of doing matrix inversion via computation, we could directly measure the forward and adjoint field, this is *in situ* adjoint method.



Implementation of *in situ* Adjoint Method

$$\frac{dg}{d\mathbf{p}} = \frac{\partial g}{\partial \mathbf{p}} + \underbrace{(\lambda^T, \lambda^{*T})}_{\text{Backward measurement}} \underbrace{\begin{pmatrix} \frac{\partial f}{\partial \mathbf{p}} \\ \frac{\partial f^*}{\partial \mathbf{p}} \end{pmatrix}}_{\text{Forward measurement}}$$

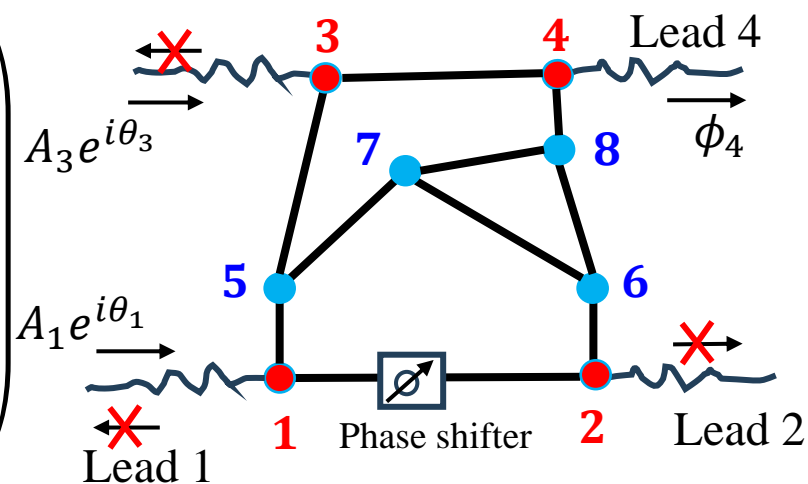
Reminder:

$$f = (M + iW^T W)\Phi - 2iW^T I_{\text{in}}$$

$$\mathbf{p} = [L_{12}, A_3, \theta_3]$$

Measure twice: forward and backward (adjoint) waves, avoid the matrix inversion!

$$\frac{\partial f}{\partial \mathbf{p}} = \begin{pmatrix} \frac{k\phi_1}{\sin^2 kL_{12}} - \frac{k \cos kL_{12} \phi_2}{\sin^2 kL_{12}} & 0 & 0 \\ \frac{k\phi_2}{\sin^2 kL_{12}} - \frac{k \cos kL_{12} \phi_1}{\sin^2 kL_{12}} & 0 & 0 \\ 0 & -2ie^{i\theta_3} & iA_3 e^{i\theta_3} \\ 0 & 0 & 0 \\ \vdots & \vdots & \vdots \\ 0 & 0 & 0 \end{pmatrix}$$



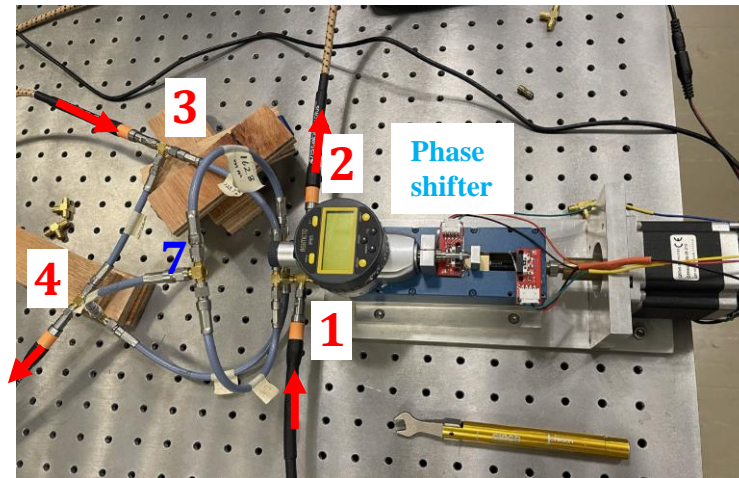
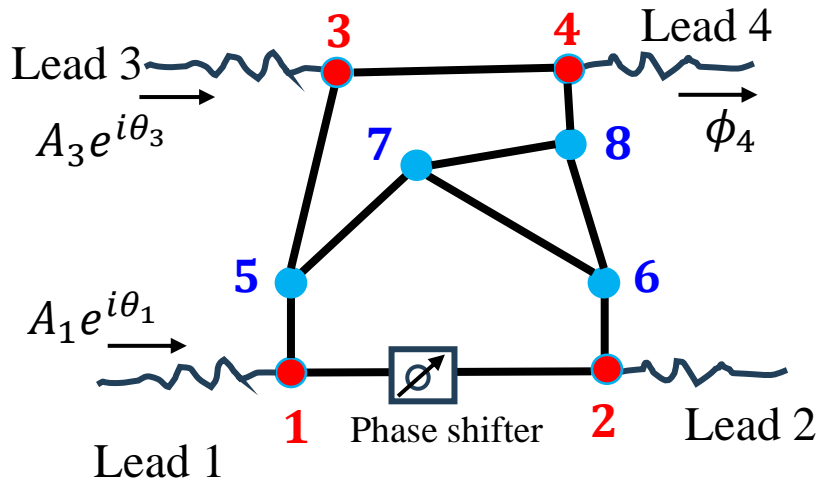
- We only need to measure the vertices local to our parameters!
- Tuning the system locally can change the system dramatically due to wave chaos!



Outline

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Example Modality 1: Targeted Mode Transmission



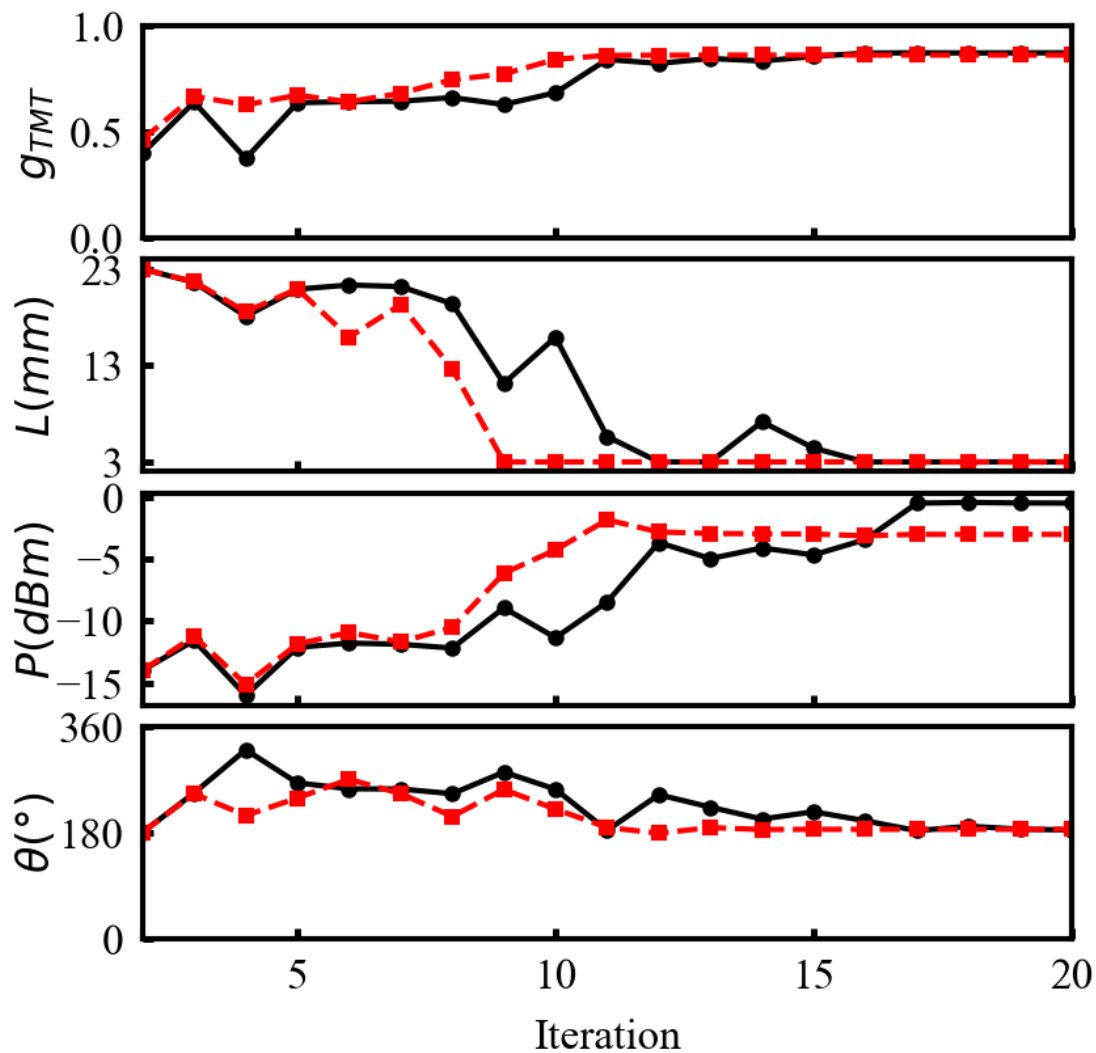
1. Forward Measurement
 - Inject signals into the system and measure the forward response.
2. Adjoint Measurement
 - Construct input based on the forward step and measure the adjoint response.
3. Gradient Calculation
 - Use measured forward and adjoint fields to calculate $\frac{dg}{dp}$
4. Parameter Update
 - Apply gradient-based optimization (e.g. MMA) and adjust phase shifter length and relative phase/amplitude
5. Iteration & Convergence
 - Repeat steps 1-4 until the objective function reaches a local min/max.



Example Modality 1: Targeted Mode Transmission

Maximize the objective function:

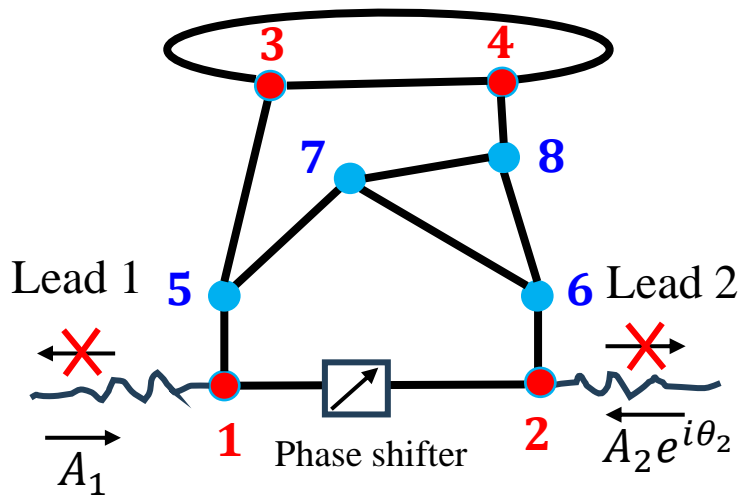
$$g = \frac{|\phi_4|^2}{A_1^2 + A_3^2} = \frac{\phi_4 \phi_4^*}{A_1^2 + A_3^2}$$



	In situ adjoint	Digital twin
Objective: g	0.873	0.862
$L(\text{mm})$	3.00	3.00
Power(dBm)	-0.47	-2.99
Phase($^{\circ}$)	184.6	185.1



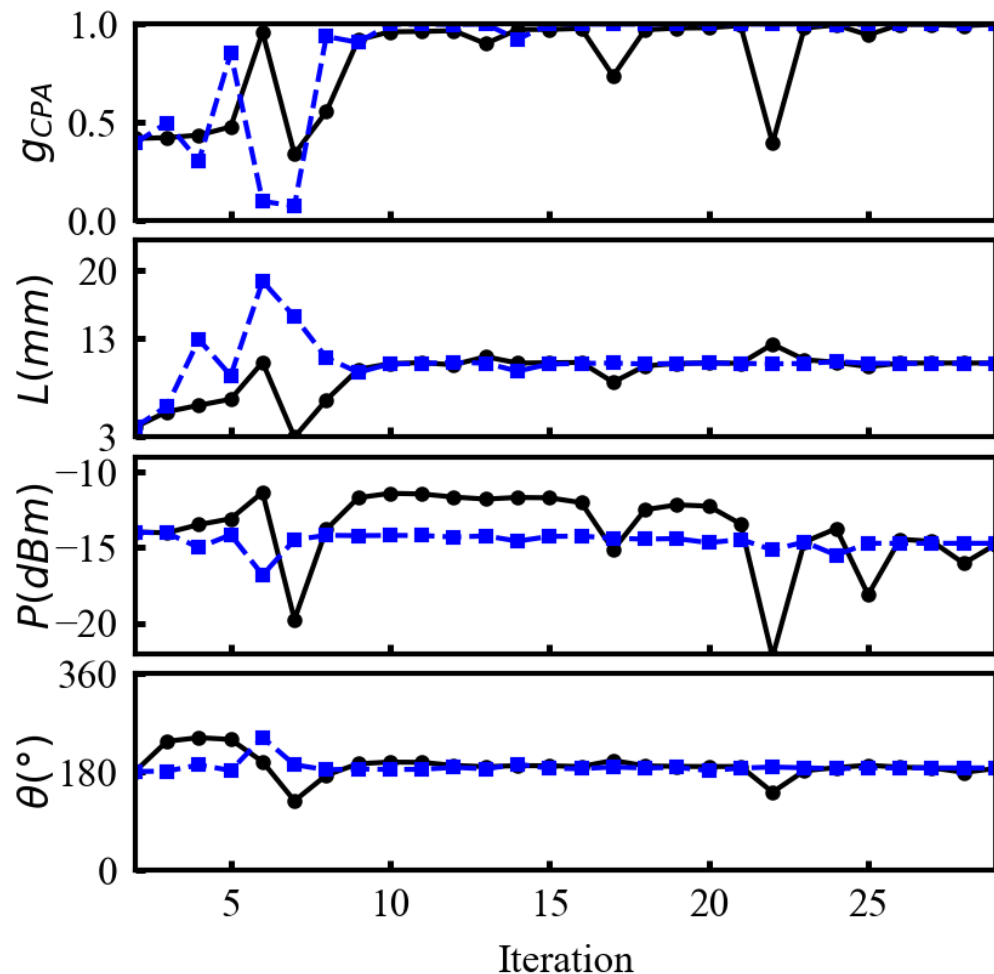
Example Modality 2: Coherent Perfect Absorption



Maximize the objective function (absorption):

$$g = 1 - \frac{|\phi_1 - A_1|^2 + |\phi_2 - A_2 e^{i\theta_2}|^2}{A_1^2 + A_2^2}$$

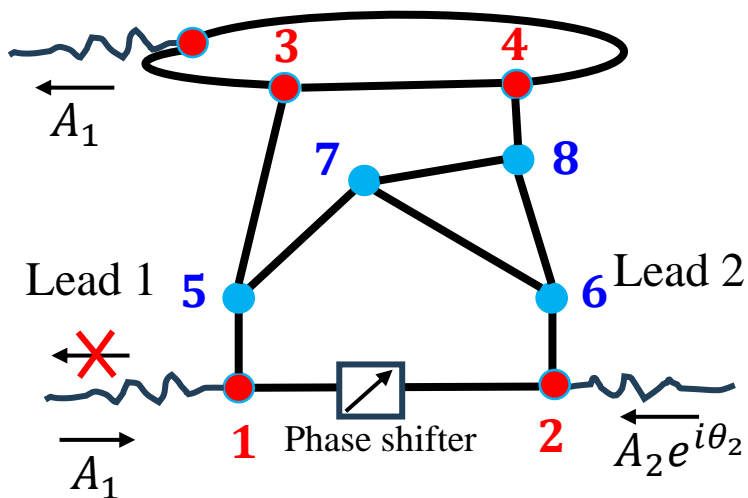
	In situ adjoint	Digital twin
Objective: g	0.999	0.999
$L(\text{mm})$	10.52	10.48
Power(dBm)	-14.82	-14.72
Phase($^\circ$)	185.2	186.4





Example Modality 3: Invisibility

Lead 3



Minimize the objective function (difference):

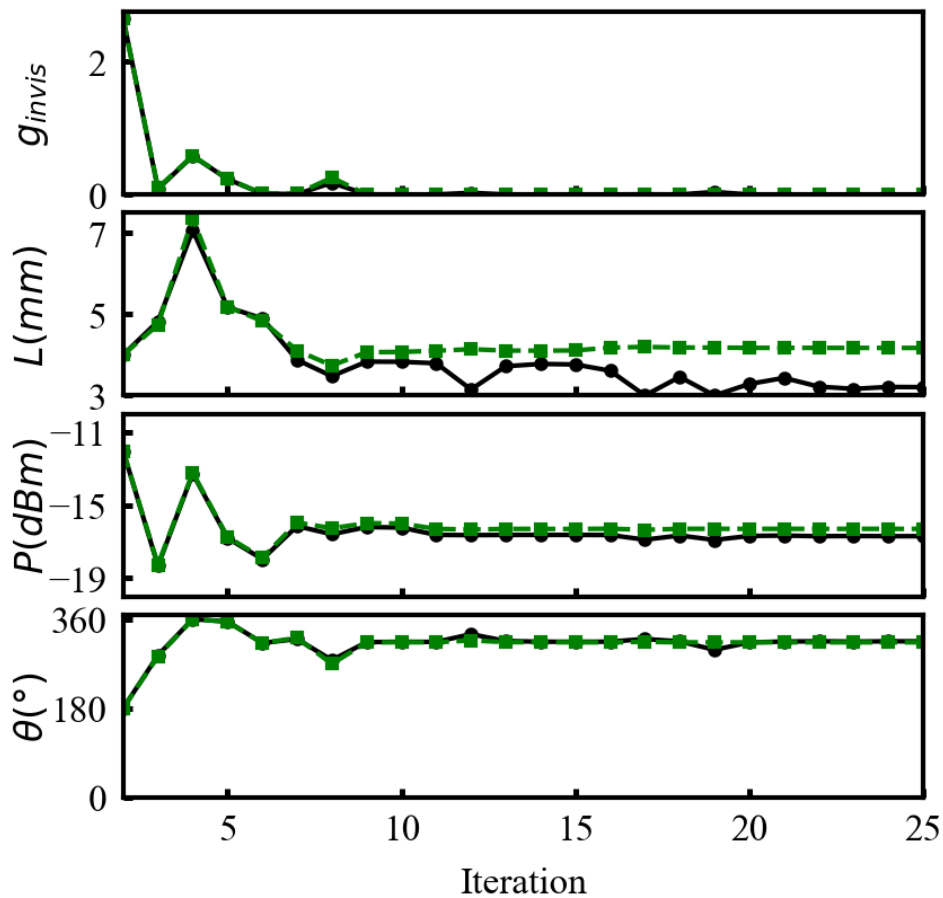
$$g_{invis} = \frac{|\phi_3 - A_1|^2}{A_1^2} + \frac{|\phi_1 - A_1|^2}{A_1^2 + A_2^2}$$

	In situ adjoint	Digital twin
Objective: g	1.65e-5	4.73e-7
$L(\text{mm})$	3.19	4.17
Power(dBm)	-16.71	-16.30
Phase($^\circ$)	315.1	313.0

a1(dBm)	a1(DEG)
-15.0079	-90.5411

b3(dBm)	b3(DEG)
-14.9878	-90.6914

b1(dBm)
-66.7887



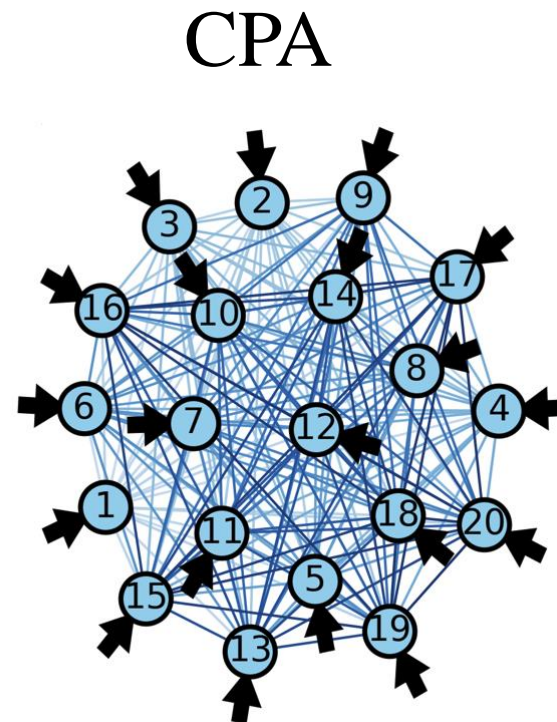
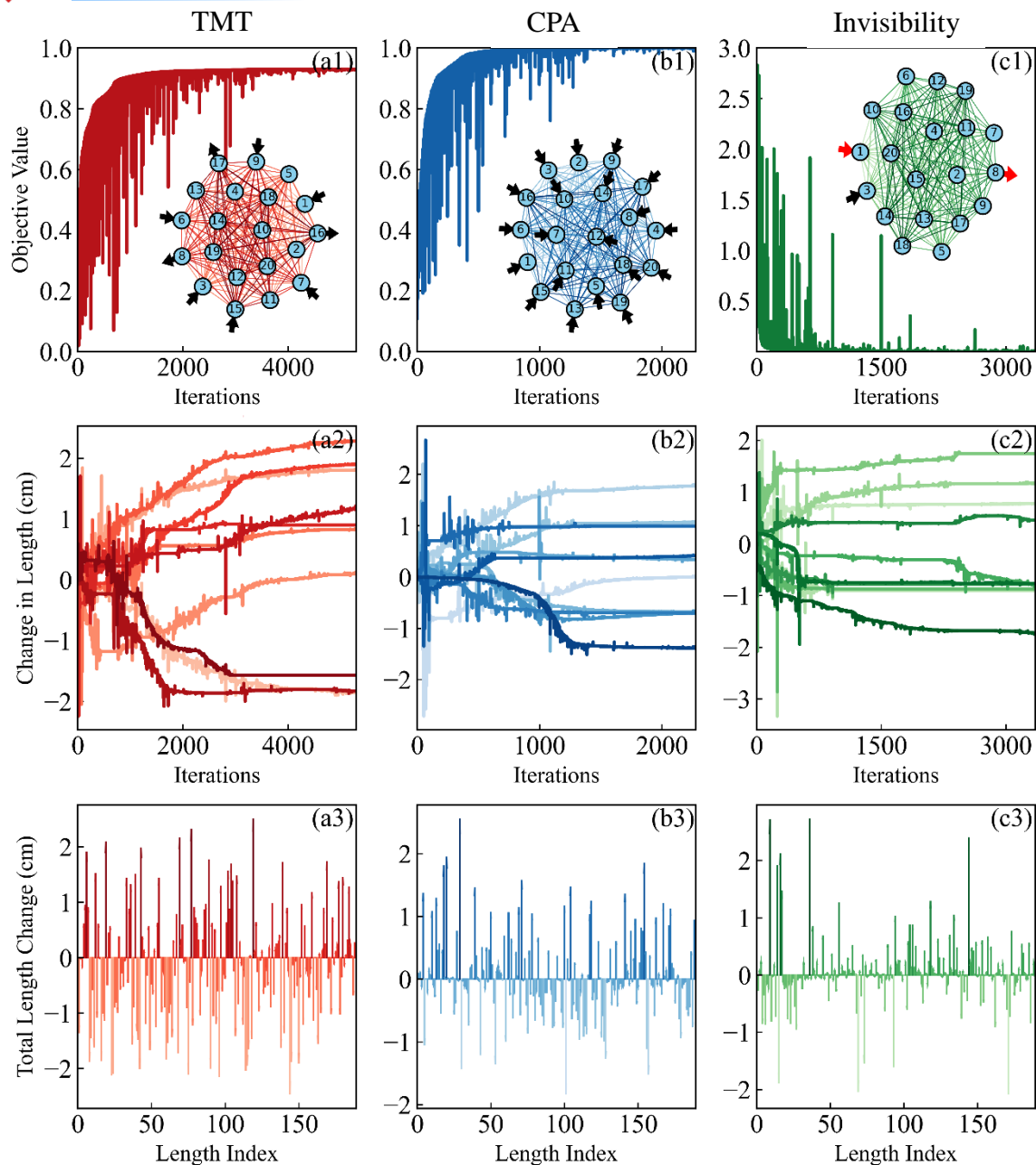


Outline

- General Problem: Challenges in Wireless Communications
- Methodologies
 1. Time-Reversal Mirror Protocol
 2. Linear and Nonlinear Wavefront Shaping Protocols
 3. Cavity Shaping Protocols
- In-Situ Adjoint Method
 1. General Principles of Adjoint Method
 2. Physical Implementation in Complex Networks
- In-Situ Modality Examples
 1. Targeted Mode Transmission
 2. Coherent Perfect Absorption
 3. Invisibility
- **In-Silico Generalization**
- Outlook



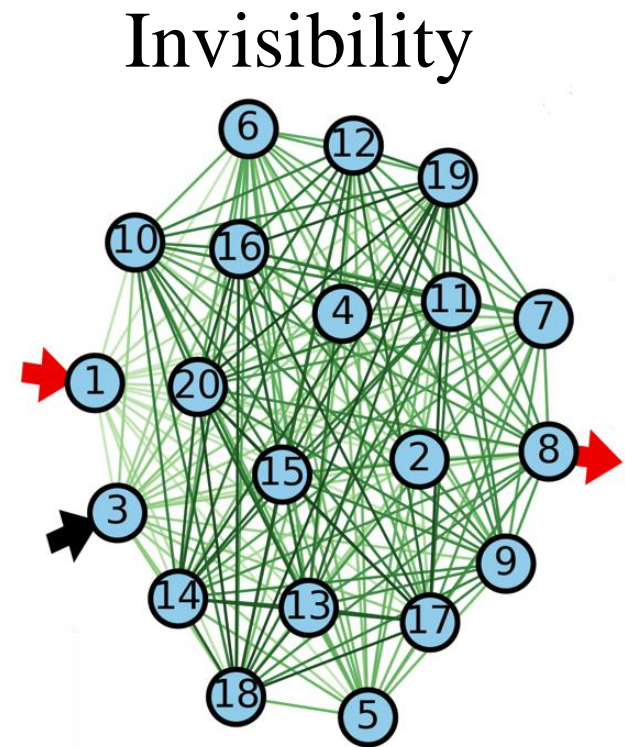
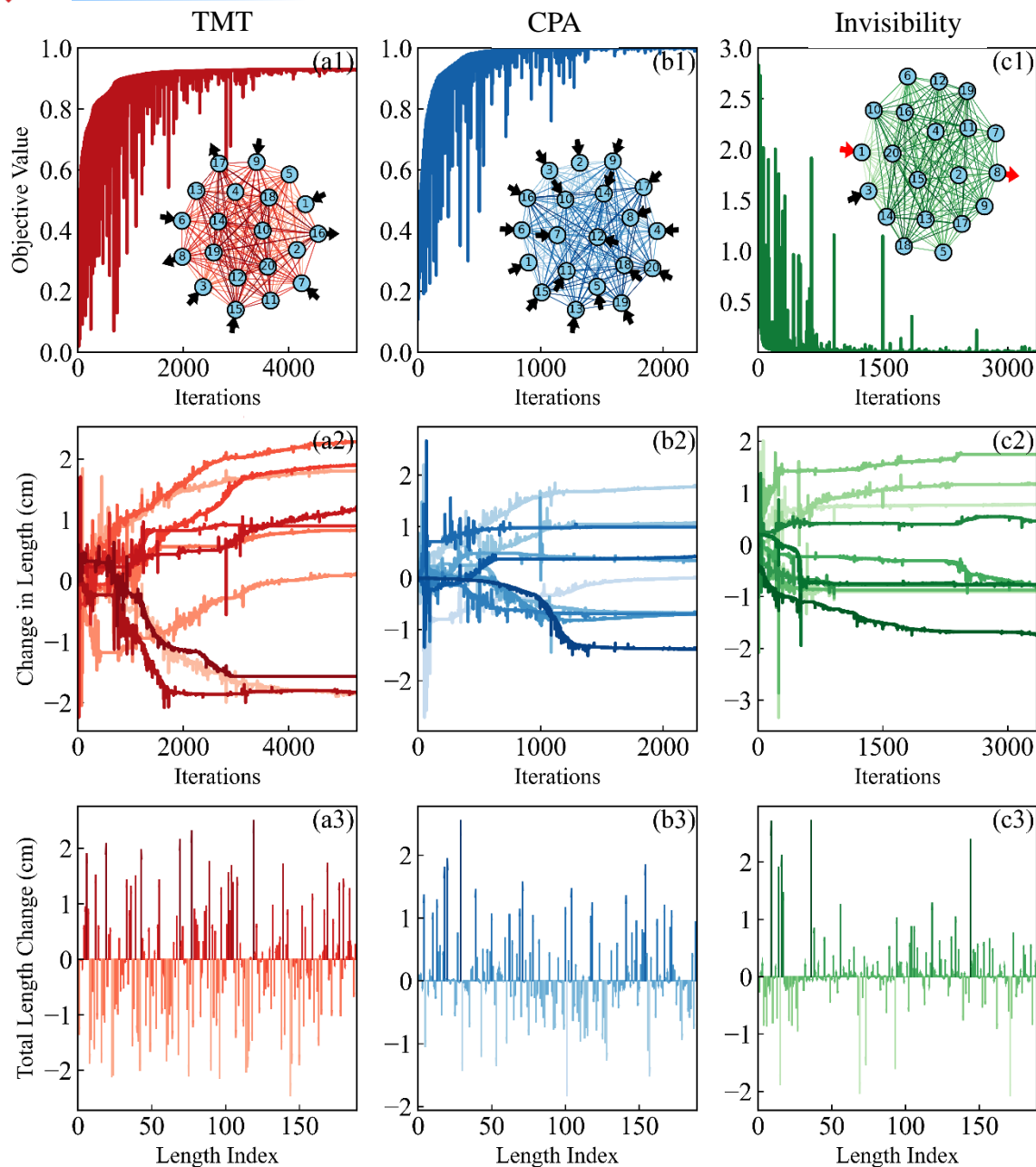
In-Silico (simulations) Using Large Complex Networks



For a fully connected graph:
 $\# \text{ of Bonds} = \frac{n(n-1)}{2} \approx n^2,$
In-Situ Adjoint only requires n
local measurements!
 $190 \text{ bonds} \rightarrow 20 \text{ measurements!}$



In-Silico (simulations) Using Large Complex Networks



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