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Three Decades of Wireless Optimization - Foundations Toward xG

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Acknowledging Collaborators and Third-Party Funding

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„I did it my AI-way“

Disclaimer: The following slides present a subjective selection and point of view on an extremely large body of work. There is no claim of completeness.

Is Wireless Optimization Important at all?

Yes, because all wireless systems have parameters that can be optimised.

I can simply use CVX, PyTorch, SCIP, Gurobi, or even ask an LLM to generate the optimization model and the solver code.

The tools either do not find the global optimum or they do not exploit domain knowledge.

But does that matter in practice? Wireless systems are complicated and uncertain. And a solution 2% away from optimum computed fast is valuable. And regarding domain knowledge, AI can absorb that from data.

But how do you know that you are 2% away from the optimum if you do not know the global optimum?
And the engineer will never find out the structure, because the trained AI is a black box.

Fair point — but maybe interpretability is overrated. If a black-box AI consistently achieves better KPIs than handcrafted optimization approaches, why should we insist on understanding the internal structure? Maybe the future engineer is less a mathematician and more a “system orchestrator” who combines datasets, simulators, pretrained models, and solver libraries. The need for deep optimization theory could become as niche as manually designing FFT hardware became after DSP libraries appeared.

Optimization knowledge is what allows engineers to distinguish between a solution that works and a solution that can be trusted, generalized, and improved.

Wireless Generations - Changing Optimization Problems

1G	2G	3G	4G	5G	6G
1980	1992+	2002+	2012+	2020+	2030+

	2G	3G	4G	5G	6G/xG
Objective	Connectivity	Spectral Efficiency	Network Utility	Reliability and Latency	Resilience and Intelligence
Opt.-Vars	Power / Codes	Beamformers	Interference Levels	Distributed Resources	Propagation Environments
Uncertainty	Noise	CSI	Interference Coupling	Dynamics	Physical-Digital Coupling
Structure	Detection Theory	Convex Programming	Distributed Optimization	Robust/Stochastic Opt.	Physics-Aware Learning

The Growing Optimization Problem

Early generations

$$\max_{P \geq 0} R(x)$$

$$\text{s.t. } P \leq P_{max}$$

- single link,
- static channel,
- asymptotic metrics,
- centralized optimization.

xG - systems

$$\max_{\mathbf{x}} [R, L, E, S, \mathcal{R}]$$

- R: rate,
- L: latency,
- E: energy efficiency,
- S: sensing quality,
- $\mathcal{R}$: resilience.

subject to

- communication constraints
- sensing constraints
- energy constraints
- reliability constraints
- electromagnetic constraints

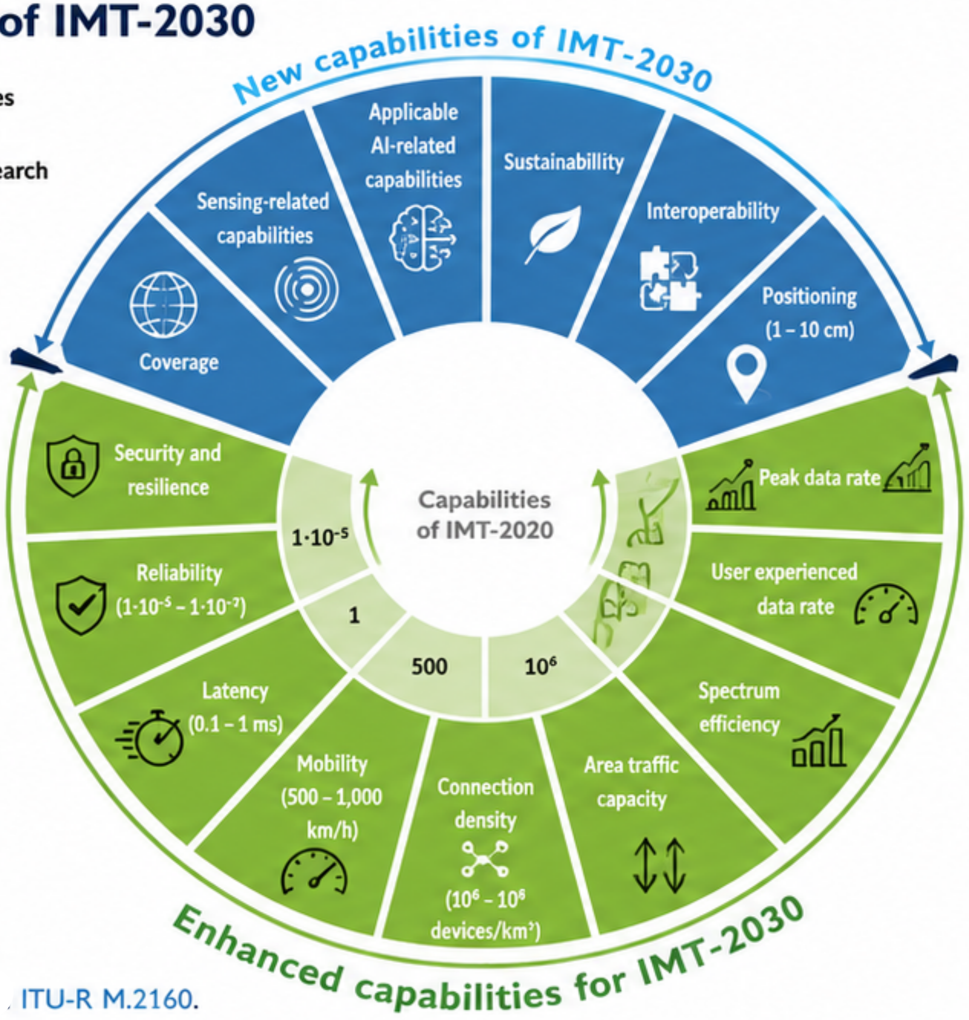
Y.-F. Liu, T.-H. Chang, M. Hong, Z. Wu, M.-C. Su, E. Jorswieck, W. Yu, "A Survey of Recent Advances in Optimization Methods for Wireless Communications", IEEE Journal on Selected Areas in Communications, vol. 42, no. 11, pp. 2992 - 3031, Nov. 2024.

Evolution of KPIs and Uncertainty

CSI Uncertainty | Noise

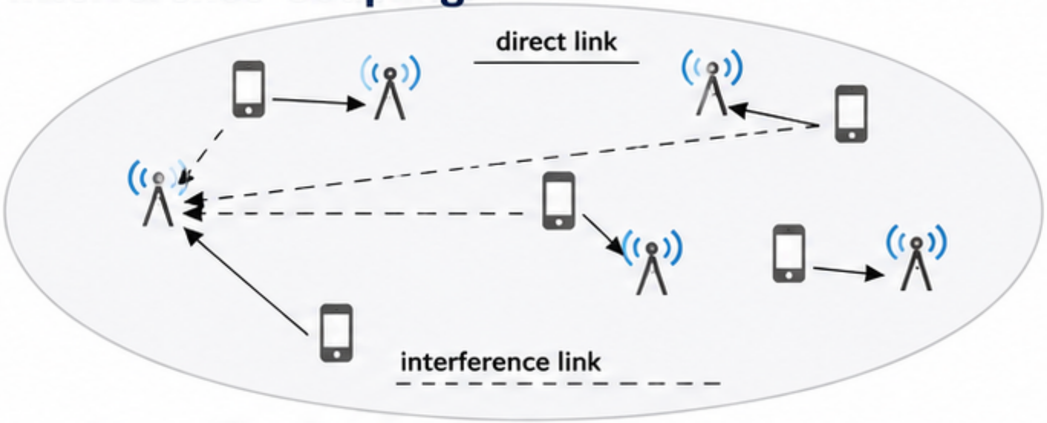
Capabilities of IMT-2030

NOTE: The range of values given for capabilities are estimated targets for research and investigation of IMT-2030.

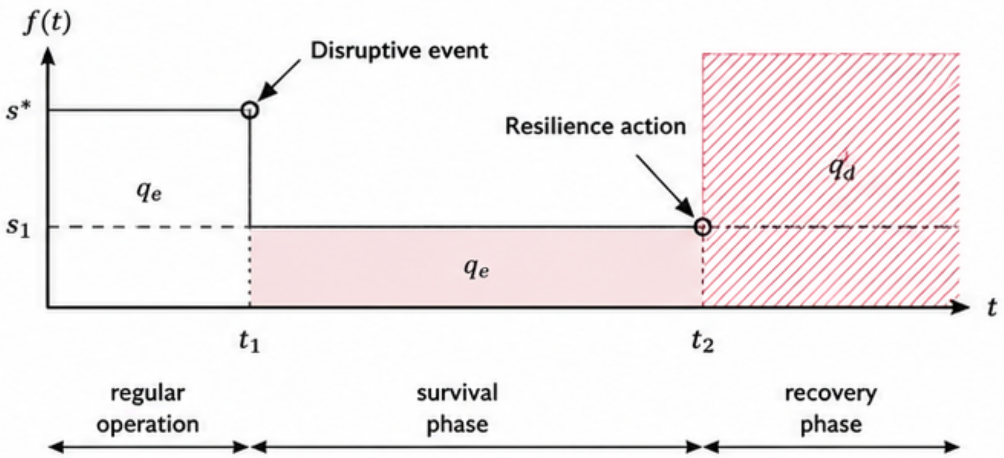


Adapted from ITU-R M.2160.

Interference Coupling



Resilience Under Disruptions



Roadmap of the Talk

Era	Main Transition	Dominant Mathematical Theme
I. MIMO and Multiuser Systems	Signals - Spatial Processing	Convexity and Achievable Rate Regions
II. Interference Networks	Links - Coupled Systems	Distributed Optimization and Games
III. Beyond Throughput	Rate - Multi-Objective Design	Robustness, Energy and Safety
IV. Toward xG	Channels - Programmable Environment	Resilience, EM Theory and Learning

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The Canonical MIMO Optimization Problem

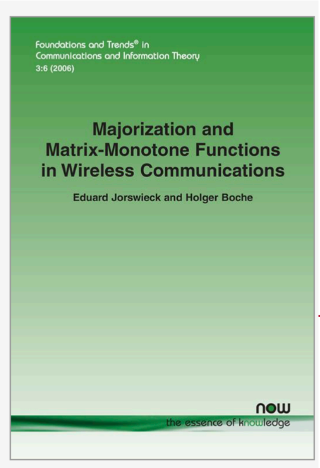
$$\max_{\mathbf{Q}\succeq 0} \ \mathrm{tr}\, \Phi\left(\mathbf{H}\mathbf{Q}\mathbf{H}^H\right)$$

$$\text{s.t. } \mathrm{tr}(\mathbf{Q}) \leq P$$

$$\mathbf{Q}^* = \mathbf{V}^H \mathrm{diag}(p_1, ..., p_N)\mathbf{V}$$

$$p_k^* = \left(\frac{1}{\lambda_k}\tilde{\phi}^{[1]}\left(\frac{\nu}{\lambda_k}\right)\right)^+$$

- Optimization variable ***Q*** - transmit covariance matrix
- Channel ***H*** to be known (estimated)
- Objective function is trace of matrix-monotone (and matrix-concave) function
  - Specializes to rate $\phi(x) = \log(1+x)$
  - and average MSE $\phi(x) = \dfrac{x}{1+x}$
  - and other metrics
- Convex programming problem - „easy“
- Solution principle: spatial mode allocation (SVD) and waterfilling



E. Jorswieck, H. Boche (2007), "Majorization and Matrix-Monotone Functions in Wireless Communications". Foundations and Trends in Communications and Information Theory, Vol. 3 No. 6 pp. 553–701, doi: https://doi.org/10.1561/0100000026

From Point Optimum to Pareto Boundary

- **Multiple objectives** (conflicting)
- Achievable rate region

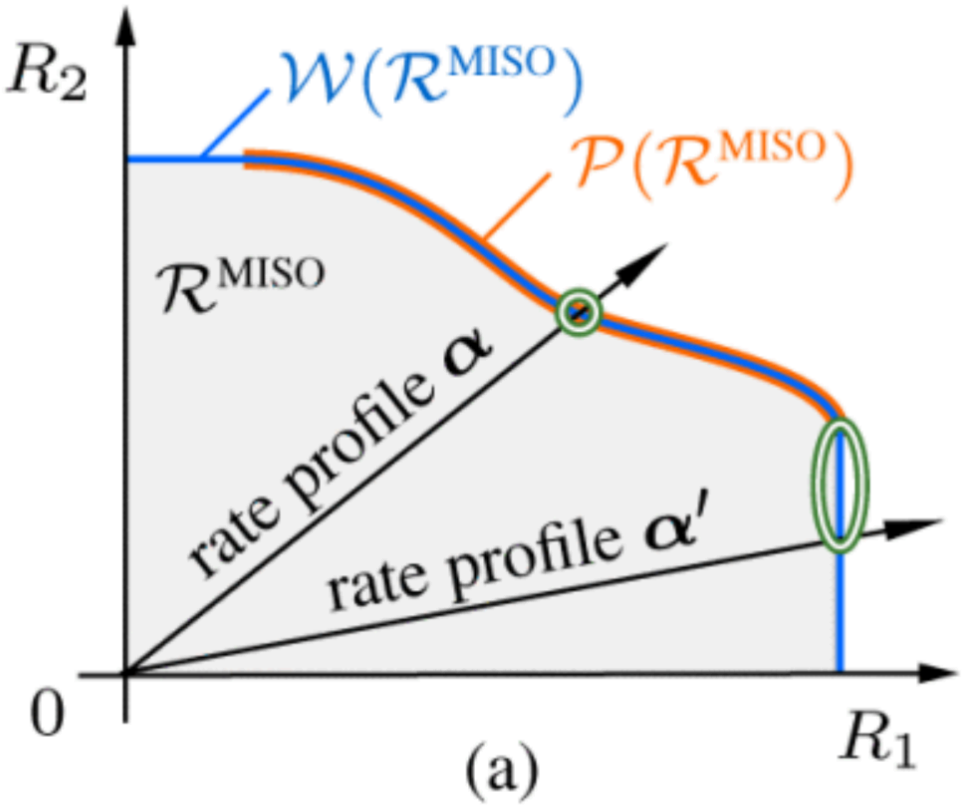
$$\mathcal{R} = \{(R_1, \ldots, R_K) : R_k \le R_k(\mathbf{Q}_1, \ldots, \mathbf{Q}_K)\}\,.$$

- Boundary obtained by

$$\max_{\mathbf{Q}_1, \ldots, \mathbf{Q}_K} \sum_{k=1}^{K} w_k R_k$$

- (if convex region) or

$$\max \ \min_k \frac{R_k}{\alpha_k}$$



A. Goldsmith, S. A. Jafar, N. Jindal and S. Vishwanath, "Capacity limits of MIMO channels," in IEEE Journal on Selected Areas in Communications, vol. 21, no. 5, pp. 684-702, June 2003, doi: 10.1109/JSAC.2003.810294.

R. Mochaourab, P. Cao and E. Jorswieck, "Alternating Rate Profile Optimization in Single Stream MIMO Interference Channels," in IEEE Signal Processing Letters, vol. 21, no. 2, pp. 221-224, Feb. 2014, doi: 10.1109/LSP.2013.2297351.

Imperfect CSI - the First Robustness Challenge

- The CSI is usually obtained by estimating the channel ***H***.
- Therefore, it is not perfect, but suffers from estimation errors.

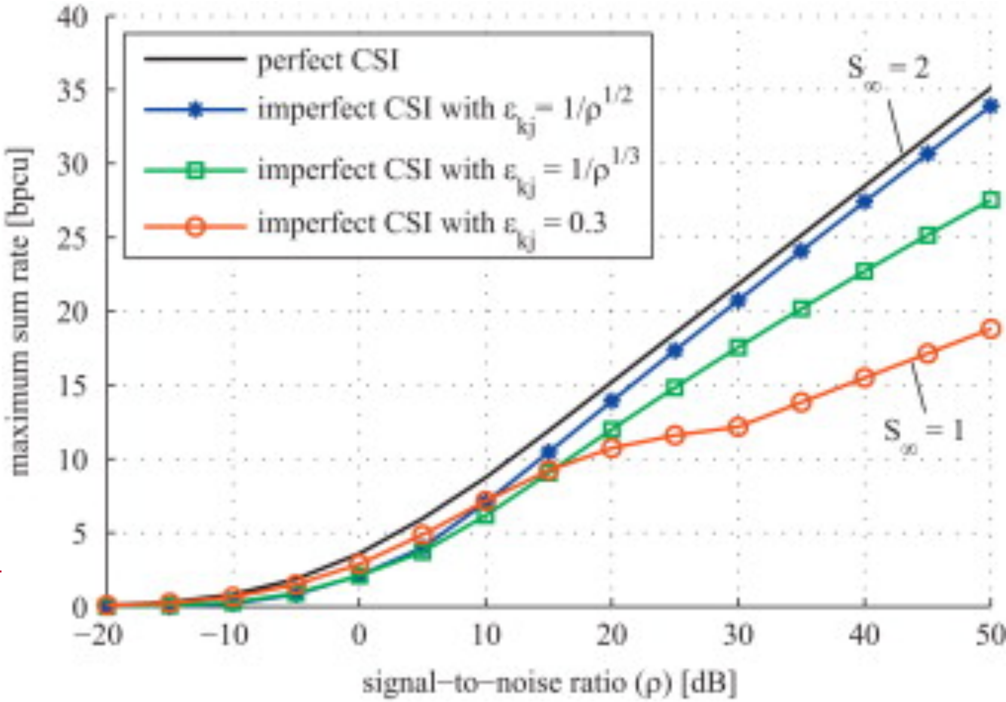
$$\mathbf{H} = \widehat{\mathbf{H}} + \Delta\mathbf{H}$$

- **Statistical uncertainty model** (estimation error is random variable)

$$\max_{\mathbf{Q}} \mathbb{E}_{\mathbf{H}}[R(\mathbf{Q}, \mathbf{H})] \quad \max_{\mathbf{Q}} \Pr\{R(\mathbf{Q}, \mathbf{H}) \geq R_0\}$$

- **Deterministic uncertainty model** (uncertainty region ***U***)

$$\max_{\mathbf{Q}} \min_{\Delta\mathbf{H} \in \mathcal{U}} R(\mathbf{Q}, \widehat{\mathbf{H}} + \Delta\mathbf{H})$$



R. Mochaourab and E. Jorswieck, "Robust Optimal Beamforming in Interference Channels with Imperfect Channel Information", Signal Processing, vol. 92, issue 10, pp. 2509-2518, Oct. 2012.

What this Era Contributed to Wireless Optimization

Dimension	Era I Contribution
Objectives	Rate, MSE, MOP, fairness
Variables	Covariance matrices, beamforming
Uncertainty	Imperfect CSI, fading
Tools	Convex optimization, matrix analysis, duality

Roadmap of the Talk

Era	Main Transition	Dominant Mathematical Theme
I. MIMO and Multiuser Systems	Signals - Spatial Processing	Convexity and Achievable Rate Regions
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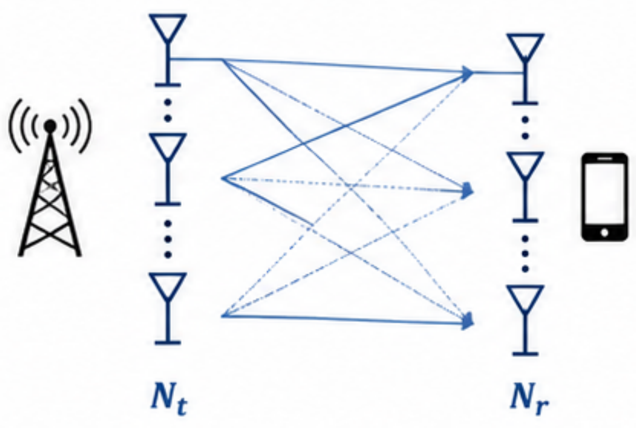
From Links to Coupled Networks

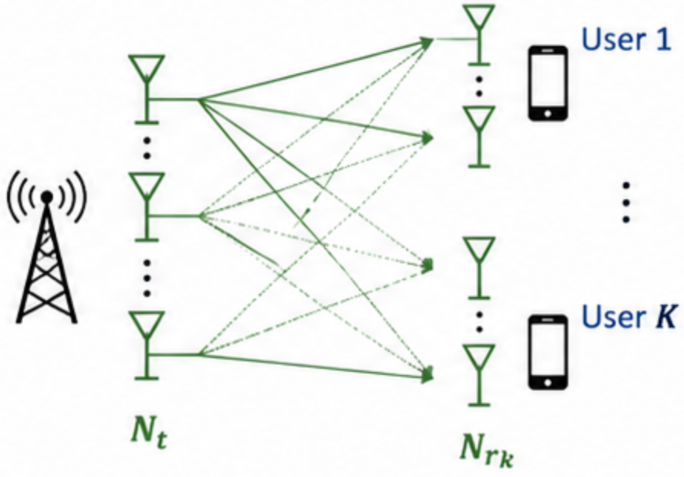
The optimization problem becomes coupled across users, cells, and decisions.

MIMO LINK



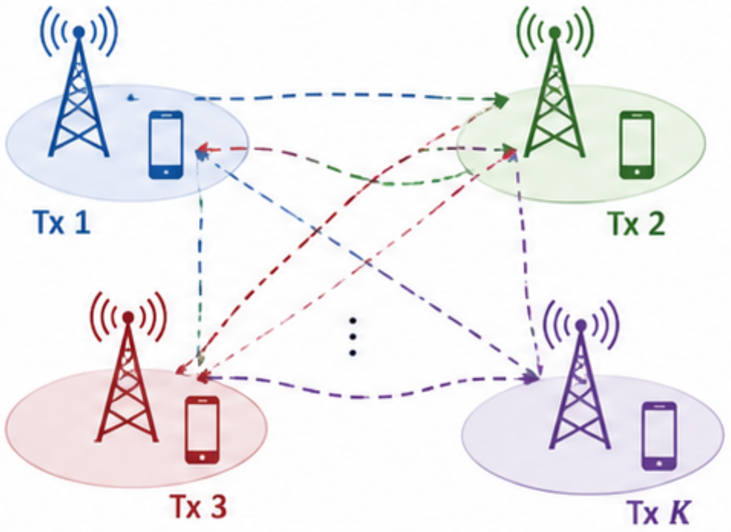
- Single transmitter–receiver pair
- Channel matrix $\mathbf{H}$
- Design: covariance / beamforming
- Objective: rate, MSE
- Optimization with (imperfect) CSI

MULTIUSER MIMO



- Multiple users served simultaneously
- Multiuser channel matrices $\mathbf{H}_k$
- Design: joint beamforming / covariance
- Objective: rate region, utility
- Centralized optimization

INTERFERENCE NETWORK



- Many links share the spectrum
- Interference couples all decisions
- Design: distributed strategies
- Objective: network utility
- Decentralized / partially coordinated

Same goal (good communication) – different world: coupling, interference, and decentralization.

Interference: Coupling Through Everyone's Decisions

Canonical formulation:

$$R_k(\mathbf{p}) = \log\left(1 + \frac{g_{kk}p_k}{\sigma_k^2 + \sum_{\ell\neq k} g_{\ell k}p_\ell}\right)$$

Multi-objective problem

Scalarization:

$$\max_{\mathbf{p}\in\mathcal{P}} \sum_{k=1}^{K} w_k R_k(\mathbf{p})$$

New problem structure:

- each power p_k helps user k,
- but hurts other users,
- objective is usually nonconvex (global programming problem)
- local decisions create global effects.

Conflicts - solutions from **game theory**

- Non-cooperative (NE, CE, …)
- Cooperative (NBS, KS, …)
- In characteristic form (Coalition formation)

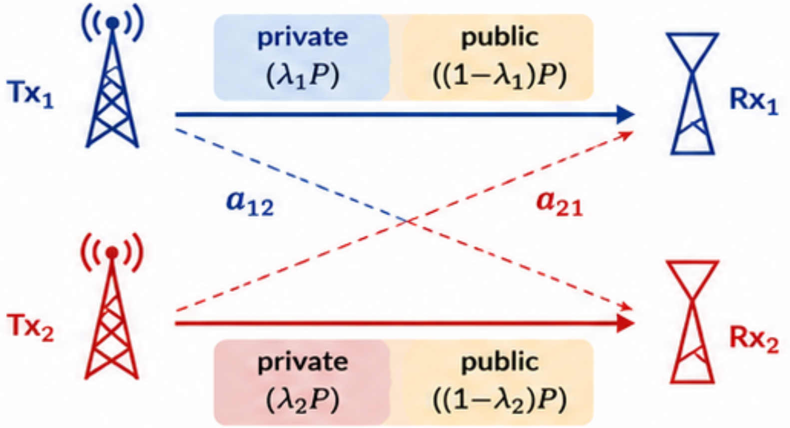
or from **microeconomics**

Shannon Meets Walras: Interference Networks as Exchange Economies

A market view on interference management and resource allocation

1. Wireless Interference Network

Two interfering links with rate splitting (Han–Kobayashi scheme)



Achievable rates (typical form)

$$R_k = f_k(\lambda_1, \lambda_2, P, a_{12}, a_{21})$$

- Rates depend on own splitting and interference from the other link
- Coupled, nonconvex optimization problem

2. Market Interpretation

Map wireless system to an exchange economy

Wireless System		Market Model
Users / links	⟷	Consumers
Resources	⟷	Goods
Achievable rates	⟷	Utilities
Power / resource constraints	⟷	Budgets
Operating point	⟷	Allocation / Equilibrium

Each user maximizes utility (rate) subject to budget

$$\max_{\mathbf{x}_k \in B_k} \; u_k(\mathbf{x}_k) \qquad \text{(individual optimization)}$$

Walras equilibrium (prices $\mathbf{q}^*$) clears the market

$$\mathbf{z}(\mathbf{q}^*) = \sum_k \mathbf{x}_k^*(\mathbf{q}^*) - \boldsymbol{\omega} = 0$$

(excess demand is zero)

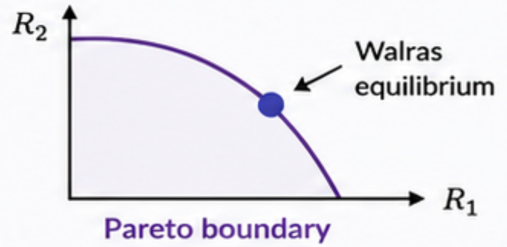
3. Main Insights

1. Distributed Coordination

Prices act as coordination signals that align decentralized decisions without centralized control.

2. Pareto Efficiency

Walras equilibrium achieves Pareto-efficient operating points in the achievable rate region.



3. Convergent Dynamics

Tatonnement process (price updates) converges iteratively to the equilibrium.

Interference management can emerge from distributed economic interaction rather than centralized control.

R. Mochaourab and E. A. Jorswieck, "Exchange Economy in Two-User Multiple-Input Single-Output Interference Channels," *IEEE JSTSP*, 2012.

E. Jorswieck and R. Mochaourab, "Walrasian Model for Resource Allocation and Transceiver Design in Interference Networks," in *Mechanisms and Games for Dynamic Spectrum Allocation*, Cambridge University Press, 2013.

Mixed-Monotonic Programming for Fast Global Optimization

1. Fundamentals

Definition

Continuous function $F : \mathbb{R}^n \times \mathbb{R}^n \mapsto \mathbb{R}$ such that

$$F(\boldsymbol{x}, \boldsymbol{y}) \le F(\boldsymbol{x}', \boldsymbol{y}) \quad \text{if } \boldsymbol{x} \le \boldsymbol{x}' \qquad \text{(Increasing in } \boldsymbol{x}\text{)}$$
$$F(\boldsymbol{x}, \boldsymbol{y}) \ge F(\boldsymbol{x}, \boldsymbol{y}') \quad \text{if } \boldsymbol{y} \le \boldsymbol{y}' \qquad \text{(Decreasing in } \boldsymbol{y}\text{)}$$

Then, F is called Mixed Monotonic (MM) Function.

$$\max_{\boldsymbol{x} \in \mathcal{D}} f(\boldsymbol{x}) \qquad \text{(MMP)}$$

$f : \mathcal{D} \mapsto \mathbb{R}$ continuous $\quad \mathcal{D} \subseteq \mathbb{R}^n$ compact, non-empty

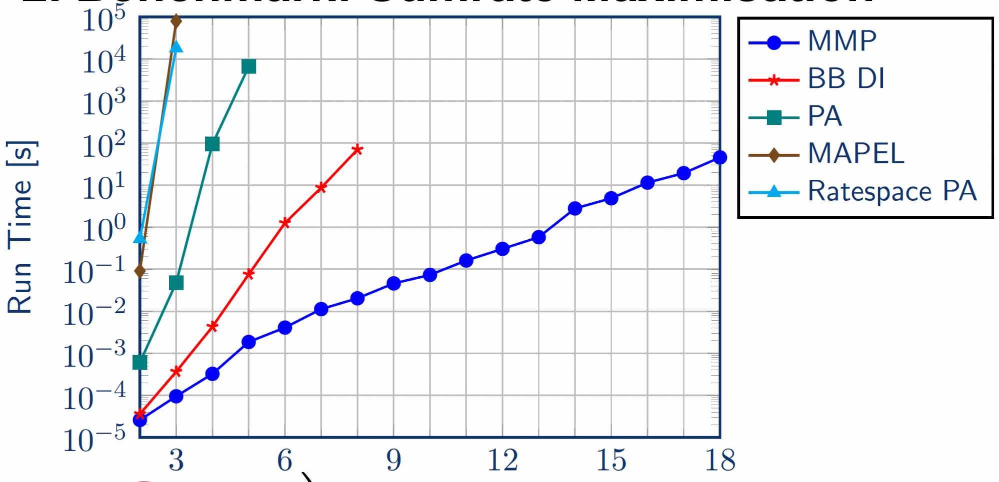
Definition

Let $\mathcal{M}_0 = [\boldsymbol{r}^0, \boldsymbol{s}^0] \supseteq \mathcal{D}$ be a box enclosing $\mathcal{D}$. Assume there exists a mixed monotonic function F on $\mathcal{M}_0$ such that

$$F(\boldsymbol{x}, \boldsymbol{x}) = f(\boldsymbol{x})$$

for all $\boldsymbol{x} \in \mathcal{M}_0$. Then, (MMP) is a mixed monotonic program.

2. Benchmark: Sumrate Maximisation



$$\sum_{k=1}^{K} \log\left(1 + \frac{g_{kk} p_k}{\sigma_k^2 + \sum_{\ell \neq k} g_{\ell k} p_\ell}\right)$$

3. Key Contributions

- **Identification** of hidden mixed monotonicity
- **Fast branch-and-bound** algorithm
- Global optimization with **guaranteed optimality**

B. Matthiesen, C. Hellings, E. A. Jorswieck and W. Utschick, "Mixed Monotonic Programming for Fast Global Optimization," in *IEEE Transactions on Signal Processing*, vol. 68, pp. 2529-2544, 2020, doi: 10.1109/TSP.2020.2983284.

Interference Optimization with NOMA

- Interference mitigation by downlink PD-NOMA

$$\mathrm{SINR}_{b,i} = \frac{g_{b,i} p_{b,i}}{\sum_{j>i} g_{b,i} p_{b,j} + I_{b,i} + \sigma^2}$$

- Optimization of powers and SIC order

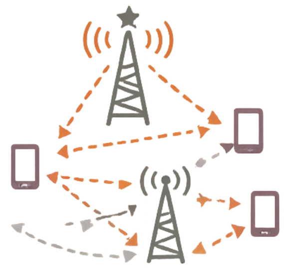
$$\max_{\pi,\mathbf{p}} \sum_{b} \sum_{i} R_{b,i}(\pi, \mathbf{p})$$

Important Observation:

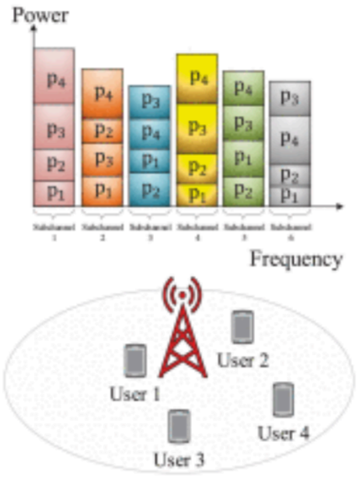
Decoding order depends on the received **SINR**, not only on the channel quality!

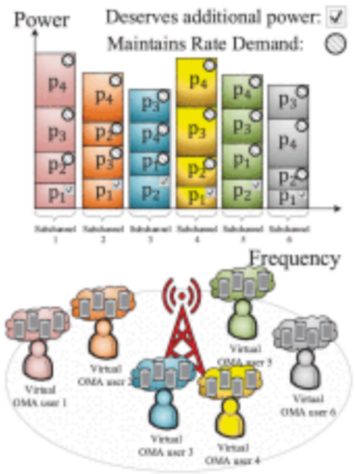
Coupled topology and resource allocation

Optimal SIC Ordering and power allocation in Multi-Cell NOMA Systems



- Power allocation changes interference patterns
- and therefore feasible SIC structures
- Power allocation changes interference patterns and therefore feasible SIC structures





S. Rezvani, E. Jorswieck, M. R. Javan, N. Mokari, "Optimal SIC Ordering and Power Allocation in Downlink Multi-Cell NOMA Systems", IEEE Transactions on Wireless Communications, vol. 21, no. 6, pp. 3553-3569, June 2022.

S. Rezvani, E. Jorswieck, R. Joda, H. Yanikomeroglu, "Optimal Power Allocation in Downlink Multicarrier NOMA Systems: Theory and Fast Algorithms", IEEE Journal on Selected Areas in Communications, vol. 40, no. 4, pp. 1162 - 1189, April 2022.

What this era contributed

Dimension	Era II Contribution
Objectives	Rate, utility, goods, prices
Variables	Distributed transmit strategies and SIC-order
Coupling	Interference and shared resources
Tools	Games, pricing, branch&bound, monotonic opt.

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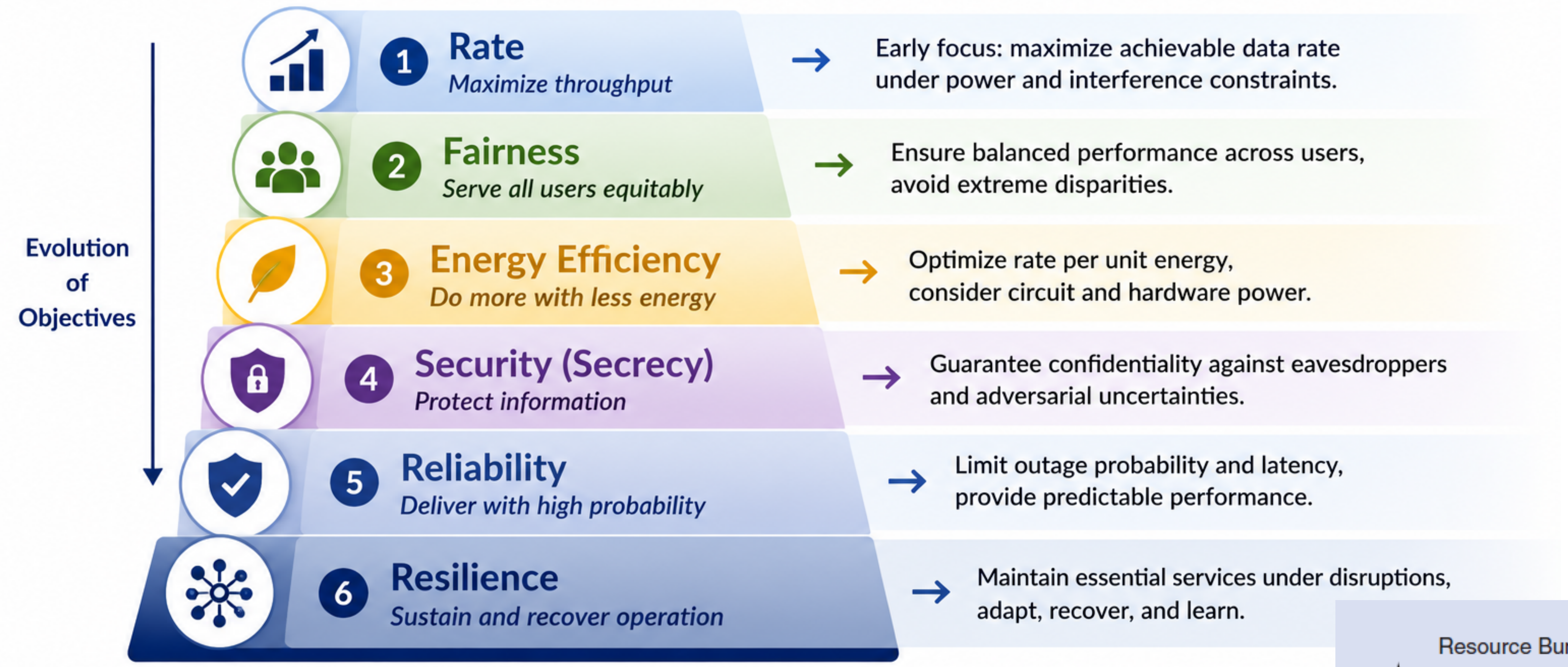
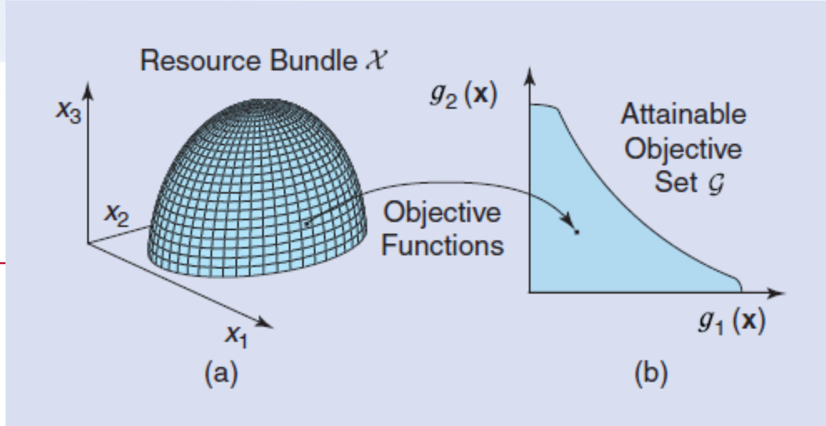
Era III: Beyond Throughput

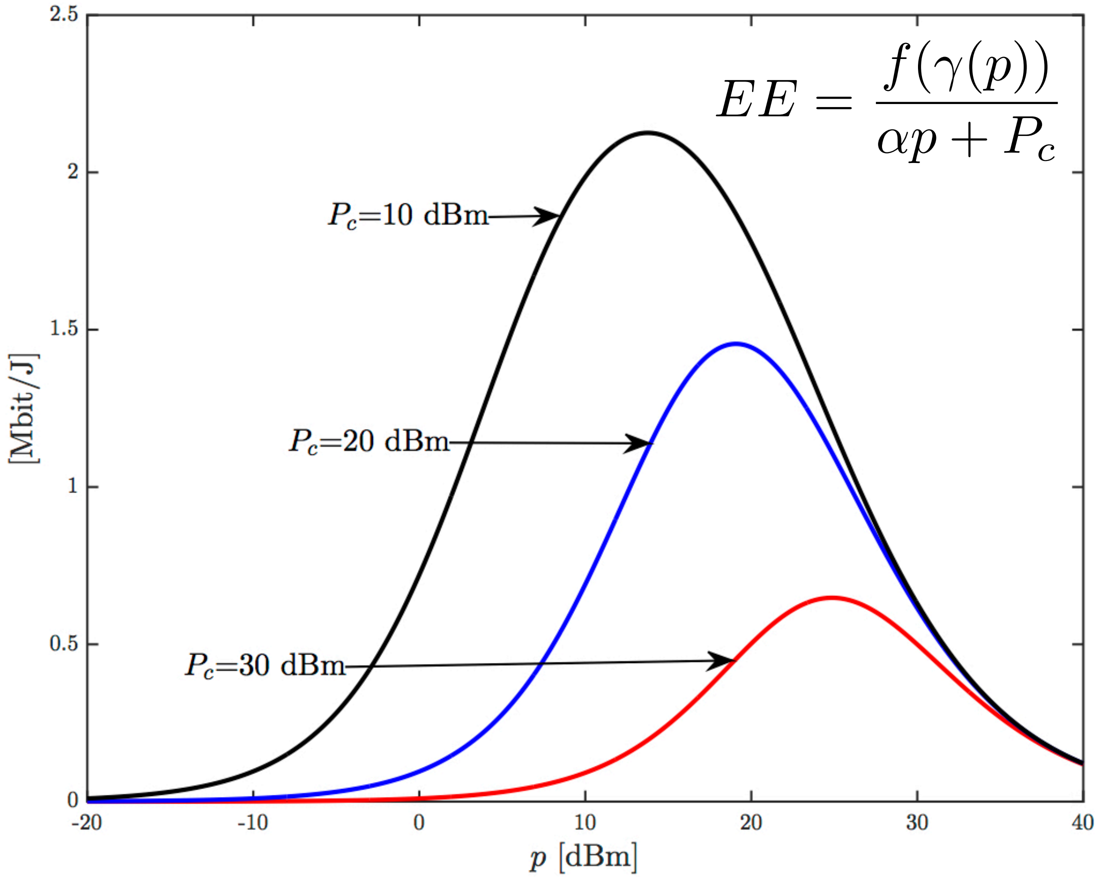


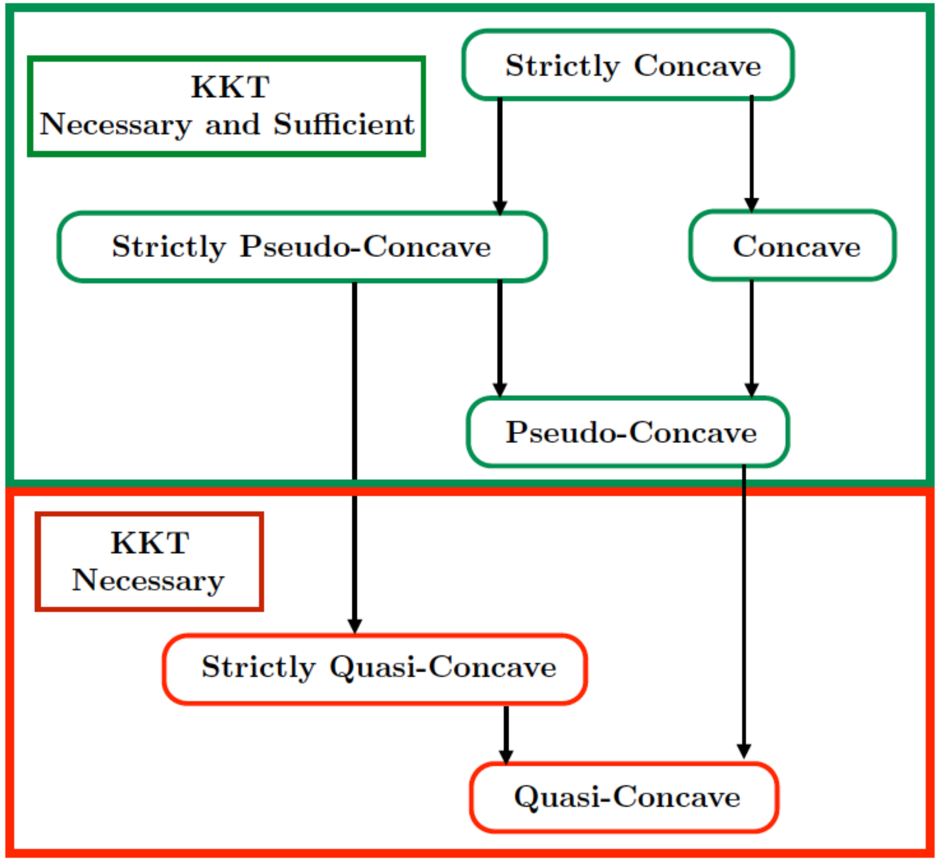
E. Björnson, E. Jorswieck, M. Debbah, B. Ottersten, "Multi-Objective Signal Processing Optimization: The Way to Balance Conflicting Metrics in 5G Systems", IEEE Signal Processing Magazine, vol. 31, no. 6, pp. 14-23, Nov. 2014.



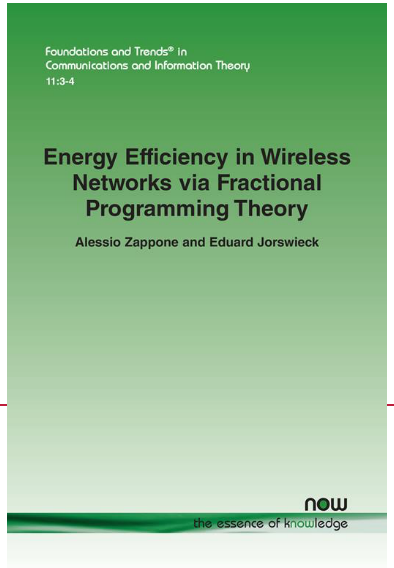
Energy-Efficient Wireless Optimization

$$\max_{\mathbf{p}} \frac{\sum_{k=1}^{K} \log(1+g_k p_k)}{\alpha \sum_{k=1}^{K} p_k + P_C}$$





$$\max_{\mathbf{p}} \sum_{k=1}^{K} \frac{\log(1+g_k p_k)}{\alpha p_k + P_C}$$



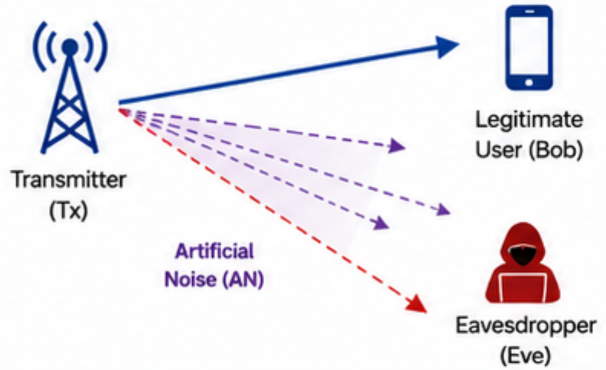
A. Zappone and E. Jorswieck, "Energy Efficiency in Wireless Networks via Fractional Programming Theory". Foundations and Trends in Communications and Information Theory, vol. 11, no. 3-4, June 2015, pp. 185-396

Optimization Under Adversarial Uncertainty

Physical-Layer Security and Trustworthy 6G Systems

1. SECURITY MODEL

Wiretap channel with adversarial eavesdropper



Achievable secrecy rate

$$R_s = [R_b - R_e]^+$$

where R_b = rate at Bob, R_e = rate at Eve

Secrecy rate maximization

$$\max_{\mathbf{Q} \geq 0} \; R_s(\mathbf{Q})$$

subject to power and QoS constraints

Classical uncertainty: stochastic (noise, fading)

Security uncertainty: adversarial (Eve is strategic)

The environment is no longer passive but potentially hostile.

2. OPTIMIZATION VIEWPOINT

From Average Performance to Secure and Robust Operation

Rate Optimization
(maximize throughput)

↓

Robust Optimization
(handle stochastic uncertainty)

↓

Adversarial Optimization
(guard against strategic attackers)

↓

Trustworthy and Resilient Systems
(secure, reliable, dependable)

Secure Beamforming
Design transmit/receive strategies to maximize secrecy rate.

Artificial Noise
Degrade Eve's channel while preserving Bob's performance.

Authentication
Leverage channel randomness for key generation and authentication.

Covert & Stealthy Communications
Limit detectability and information leakage.

Semantic / Context-Aware Security
Protect information meaning and inference.

Joint Communication and Sensing Security
Secure ISAC systems against eavesdropping and spoofing.

3. 6G-PHYSEC CONNECTION

cost
EUROPEAN COOPERATION IN SCIENCE & TECHNOLOGY

6G PHYSEC

COST Action CA22168 – 6G-PHYSEC

Physical Layer Security for Trustworthy and Resilient 6G Systems

Trustworthy 6G
Enabling secure, private, and trustworthy communication and services.

Intelligent & Resilient Systems
AI/ML-driven and adaptive security mechanisms for dynamic environments.

Quantum-Resistant Security
Developing PHY security against future quantum-enabled threats.

Scalable & Sustainable Security
Energy-efficient and resource-aware security solutions.

Experiments & Demonstrations
From theory to real-world validation and large-scale experimentation.

Join the community and learn more:
https://6gphysec.org/

Wireless optimization evolved from performance maximization toward trustworthy, secure, and resilient operation under adversarial uncertainty.

From Classical to Secure Design

Dimension	Classical Design	Secure Design
Objective	Optimize average rate	Optimize secrecy / reliability
Environment	Passive	Strategic adversary
Uncertainty	Stochastic	Adversarial

Combined Performance Metrics

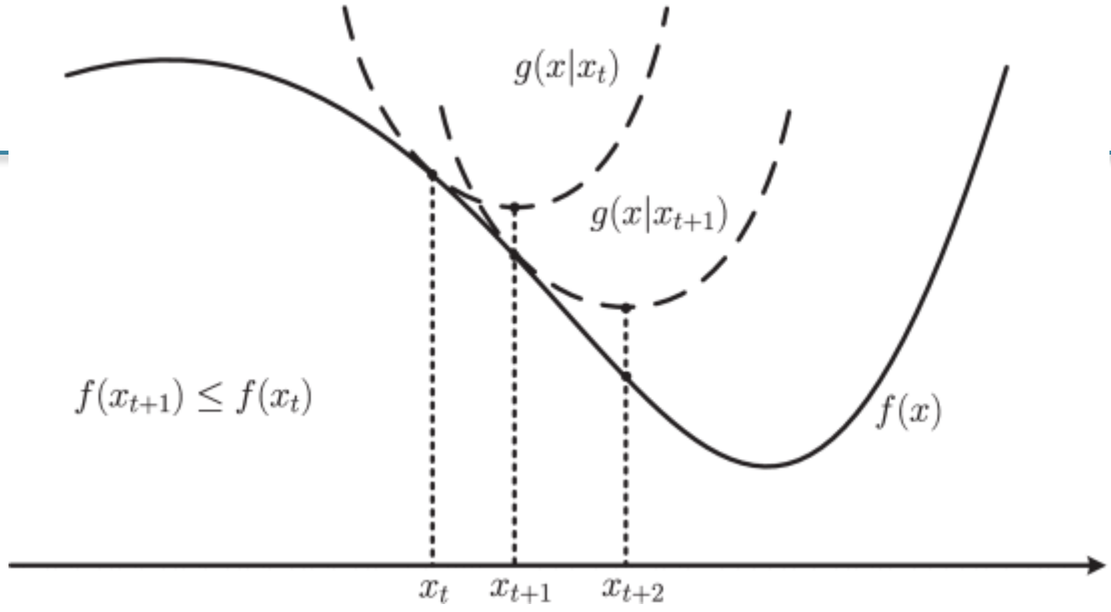
Secrecy energy efficiency

$$SEE = \frac{W \log\left(\frac{1+p\mathbf{w}^H\mathbf{h}\mathbf{h}^H\mathbf{w}}{1+p\mathbf{w}^H\mathbf{g}\mathbf{g}^h\mathbf{w}}\right)}{\mu p + P_c}$$

Secret key energy efficiency

$$SKEE = \frac{W \log\left(\frac{1+p\mathbf{w}^H(\mathbf{h}\mathbf{h}^H+\mathbf{g}\mathbf{g}^H)\mathbf{w}}{1+p\mathbf{w}^H\mathbf{g}\mathbf{g}^h\mathbf{w}}\right)}{\mu p + P_c}$$

Sequential fractional programming - be careful!



Majorization-minimization algorithms can find stationary points of global programming problems

Dinkelbach algorithm for fractional programming is guaranteed to converge if the inner problem is solved globally.

Y. Sun, P. Babu and D. P. Palomar, "Majorization-Minimization Algorithms in Signal Processing, Communications, and Machine Learning," in *IEEE Transactions on Signal Processing*, vol. 65, no. 3, pp. 794-816, 1 Feb.1, 2017, doi: 10.1109/TSP.2016.2601299.

A. Zappone, P.-H. Lin, E. Jorswieck, "Optimal Energy-Efficient Design of Confidential Multiple-Antenna Systems", IEEE Trans. on Inf. Forensics and Security, vol. 13, no. 1, pp. 237-252, Jan. 2018.

Fractional Programming Beyond Classical Ratios

Unified Fractional Matrix Programming for xG Wireless Systems

1. WIRELESS KPIs AS FRACTIONAL FUNCTIONS

Many important KPIs in xG have a fractional structure.

Energy Efficiency (EE)

$$e_k = \frac{r_k}{P_s + \eta \,\mathrm{Tr}(W_k W_k^H)}$$

r_k: rate of user k
P_s: static power
W_k: precoding matrix

Delay (Latency)

$$d_k = \frac{L_k}{r_k}$$

L_k: payload size (bits)

Channel Dispersion (FBL)

$$v_k = 2\,\mathrm{Tr}\left(S_k (D_k + S_k)^{-1}\right)$$

S_k: signal cov.
D_k: interference + noise cov.

Mean Square Error (MSE)

$$\xi_k = \mathrm{Tr}\left(I - D_k^{-1} S_k\right)$$

D_k: error cov.
S_k: signal cov.

Modern xG metrics involve sums, products, and matrix-valued fractional functions.

2. UNIFIED FRACTIONAL MATRIX PROGRAMMING (FMP) FRAMEWORK

We consider generic optimization problems (OPs):

Minimization OP

$$\min_{\{X\}\in\mathcal{X}} \sum_{m=1}^{M} \frac{f_m(\{X\})}{g_m(\{X\})}$$

Maximization OP

$$\max_{\{X\}\in\mathcal{X}} \sum_{m=1}^{M} \frac{f_m(\{X\})}{g_m(\{X\})}$$

where $f_m(\cdot)$ and $g_m(\cdot) > 0$ are arbitrary (matrix-valued) functions.

Key Idea: Surrogate Reformulation via MM Principle

Complicated Fractional Problem (non-convex, coupled, matrix-valued)
↓
Surrogate Reformulation (fractional functions → tractable surrogates)
↓
MM-Inspired Single-Loop Updates (closed-form / convex subproblems)
↓
Stationary Point (KKT conditions satisfied)

Surrogate of each ratio

$$h_m(X) = \frac{f_m(X)}{g_m(X)}$$

Surrogate at iteration z

$$\tilde{h}_m^{(z)}(X) = 2a_m^{(z)} t_m - \left(a_m^{(z)}\right)^2 g_m(X)$$

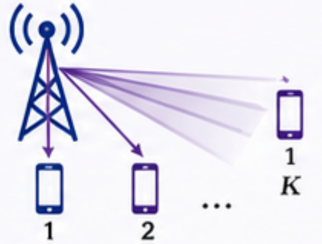
The parameters $a_m^{(z)}$ and t_m are updated analytically at each iteration.

Our Framework vs. Classical Fractional Programming Solvers

Feature	Classical FP (e.g., Dinkelbach)	Our FMP Framework
Objective / Constraint	Single ratio	Sums / products of **multiple** ratios
Optimization Variables	Scalar / vector	Matrices (complex-valued)
Algorithmic Structure	Typically twin-loop	Single-loop (MM-based)
Solvable Problem Classes	Limited	Broad class of FMP problems
Convergence	Problem-dependent	Guaranteed to stationary point

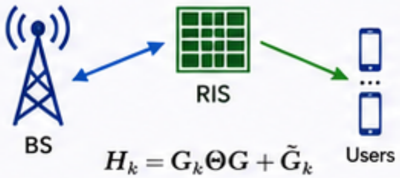
3. APPLICATIONS IN xG WIRELESS SYSTEMS

FBL MU-MIMO Systems



- Finite blocklength coding
- Low-latency (URLLC)
- Optimize EE, latency, MSE, SEE tradeoff
- Matrix variables: precoders, receive filters, power allocations

RIS-Assisted Systems



- RIS coefficient optimization (Θ)
- SEE tradeoff
- Energy-efficient beamforming

Multi-Objective Optimization

- Spectral–energy efficiency tradeoff
- Weighted sum EE / Geometric mean EE
- Sum delay minimization
- MSE minimization
- Joint optimization of communication, computation, and propagation resources

Unified optimization across communication, computation, and propagation domains for next-generation (xG) networks.

xG wireless systems require unified optimization frameworks capable of handling coupled fractional, matrix-valued, and multi-objective performance metrics.

M. Soleymani, E. A. Jorswieck, R. Schober, L. Hanzo, "A Framework for Fractional Matrix Programming Problems With Applications in FBL MU-MIMO," *IEEE Transactions on Wireless Communications*, 2026.

What Era III Contributed

Dimension	Era III Contribution
Objectives	Energy efficiency, security, robustness, resilience
Uncertainty	Stochastic and adversarial
Optimization	Multi-objective and (mixed) non-convex
New Challenge	Performance under disruptions

Roadmap of the Talk

Era	Main Transition	Dominant Mathematical Theme
I. MIMO and Multiuser Systems	Signals - Spatial Processing	Convexity and Achievable Rate Regions
II. Interference Networks	Links - Coupled Systems	Distributed Optimization and Games
III. Beyond Throughput	Rate - Multi-Objective Design	Robustness, Energy and Safety
IV. Toward xG	Channels - Programmable Environment	Resilience, EM Theory and Learning

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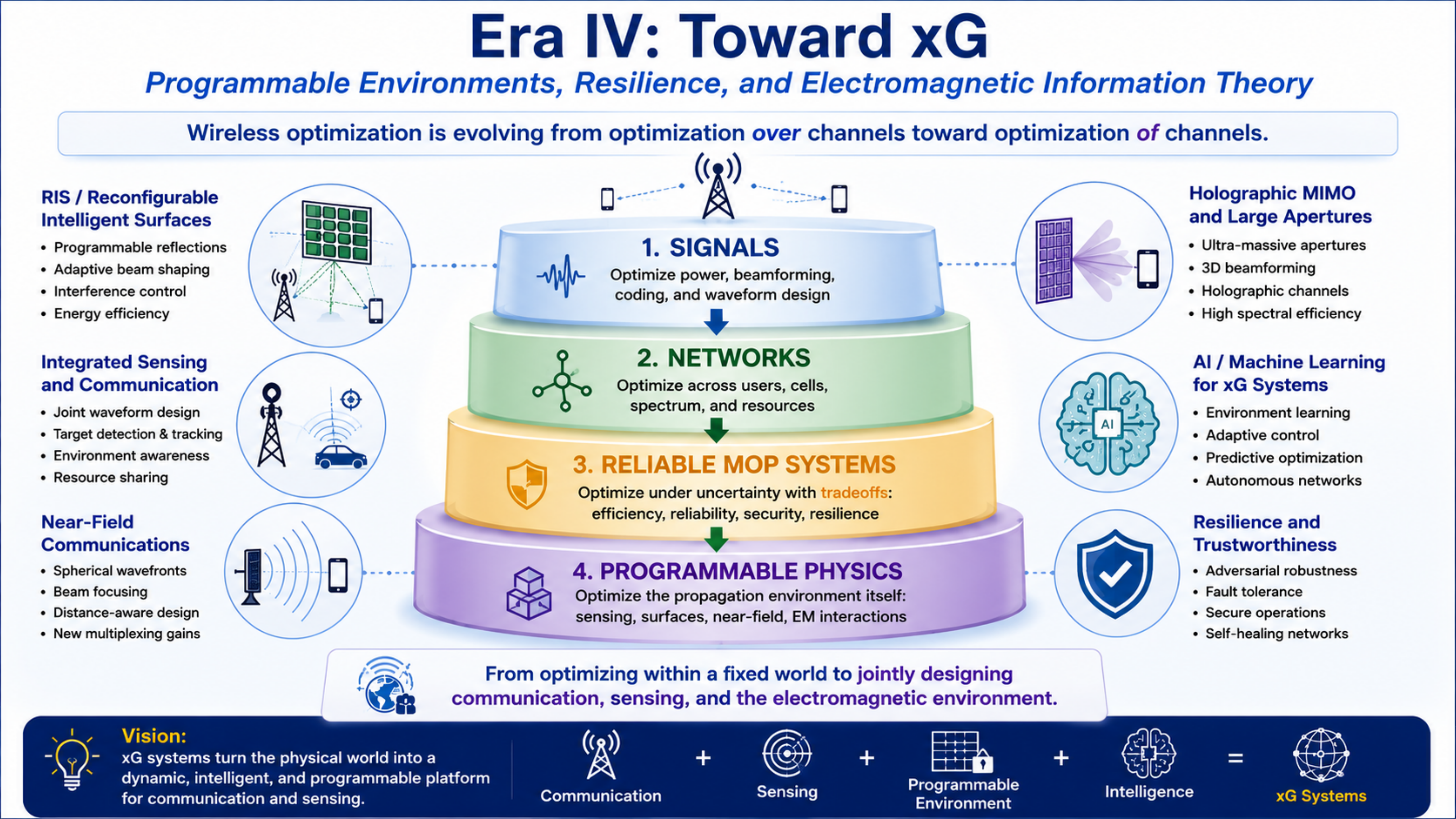
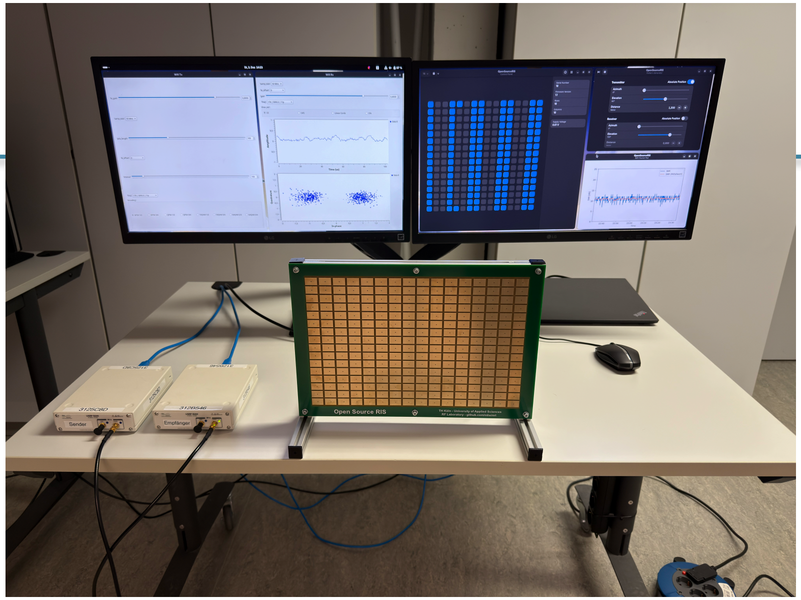
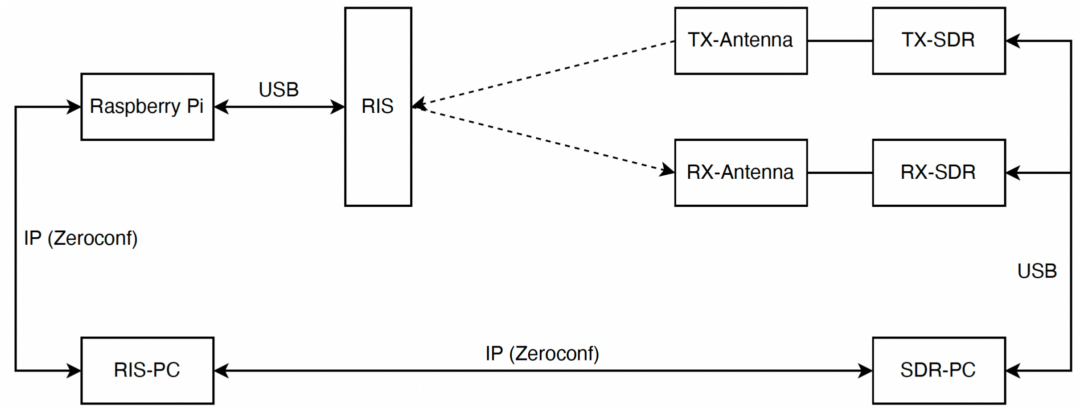
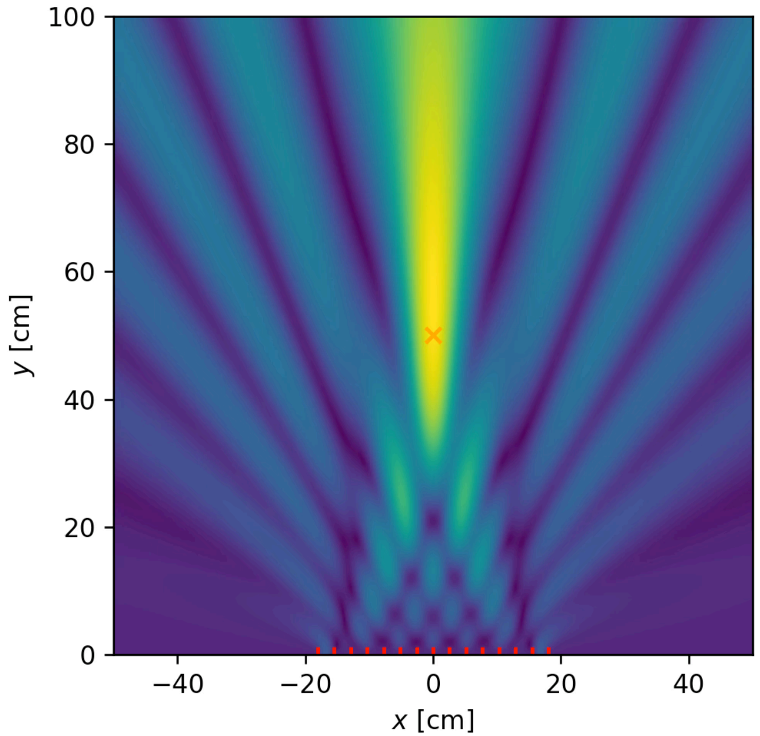

Era IV: Toward xG
Programmable Environments, Resilience, and Electromagnetic Information Theory
Wireless optimization is evolving from optimization over channels toward optimization of channels.
RIS / Reconfigurable Intelligent Surfaces
• Programmable reflections
• Adaptive beam shaping
• Interference control
• Energy efficiency
Integrated Sensing and Communication
• Joint waveform design
• Target detection & tracking
• Environment awareness
• Resource sharing
Near-Field Communications
• Spherical wavefronts
• Beam focusing
• Distance-aware design
• New multiplexing gains
1. SIGNALS
Optimize power, beamforming, coding, and waveform design
2. NETWORKS
Optimize across users, cells, spectrum, and resources
3. RELIABLE MOP SYSTEMS
Optimize under uncertainty with tradeoffs: efficiency, reliability, security, resilience
4. PROGRAMMABLE PHYSICS
Optimize the propagation environment itself: sensing, surfaces, near-field, EM interactions
Holographic MIMO and Large Apertures
• Ultra-massive apertures
• 3D beamforming
• Holographic channels
• High spectral efficiency
AI / Machine Learning for xG Systems
AI
• Environment learning
• Adaptive control
• Predictive optimization
• Autonomous networks
Resilience and Trustworthiness
• Adversarial robustness
• Fault tolerance
• Secure operations
• Self-healing networks
From optimizing within a fixed world to jointly designing communication, sensing, and the electromagnetic environment.
Vision:
xG systems turn the physical world into a dynamic, intelligent, and programmable platform for communication and sensing.
Communication
+
Sensing
+
Programmable Environment
+
Intelligence
=
xG Systems

Programmable Radio Environment with RIS

- 16 x 16 Diagonal RIS sub 5 GHz (FR1) in the lab (see ref)
- OpenSource python program for controlling 1-bit RIS elements
  - RIS near-field beam-focussing
  - Signal strength measurements







M. Heinrichs, A. Sezgin and R. Kronberger, "Open Source Reconfigurable Intelligent Surface for the Frequency Range of 5 GHz WiFi," 2023 IEEE International Symposium On Antennas And Propagation (ISAP), Kuala Lumpur, Malaysia, 2023, pp. 1-2, doi: 10.1109/ISAP57493.2023.10389095.

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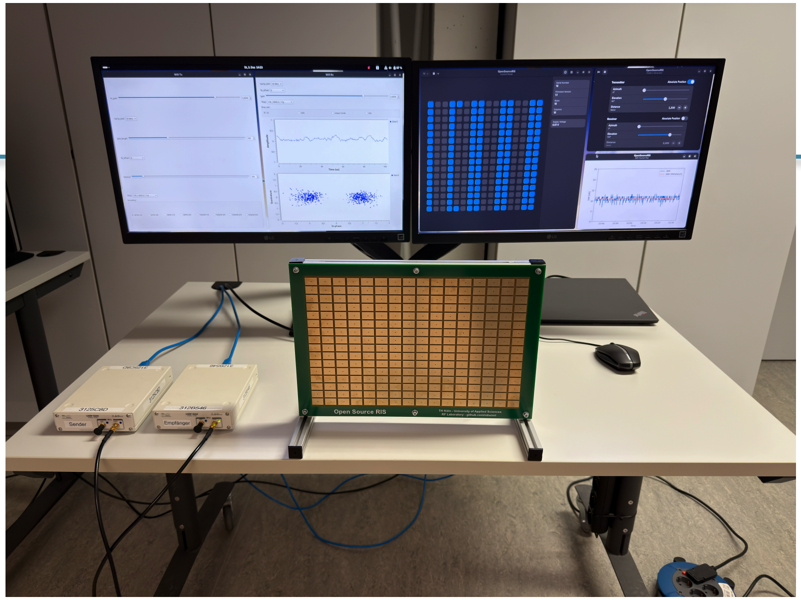

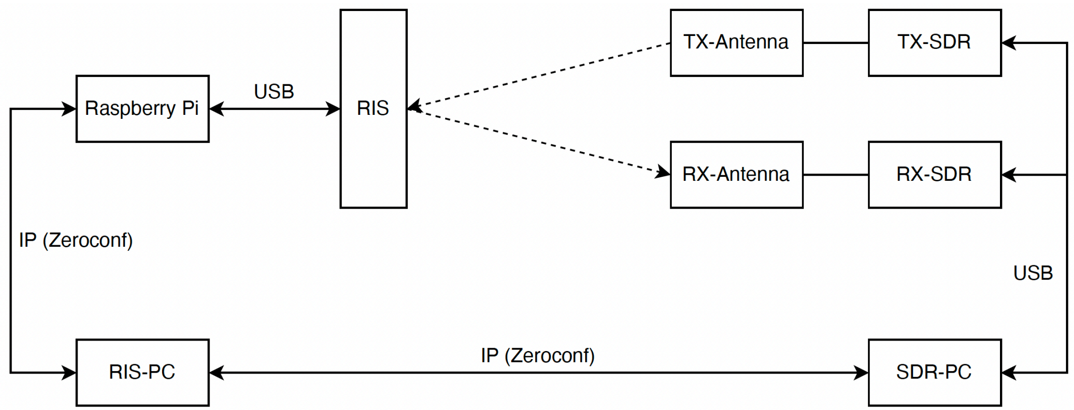

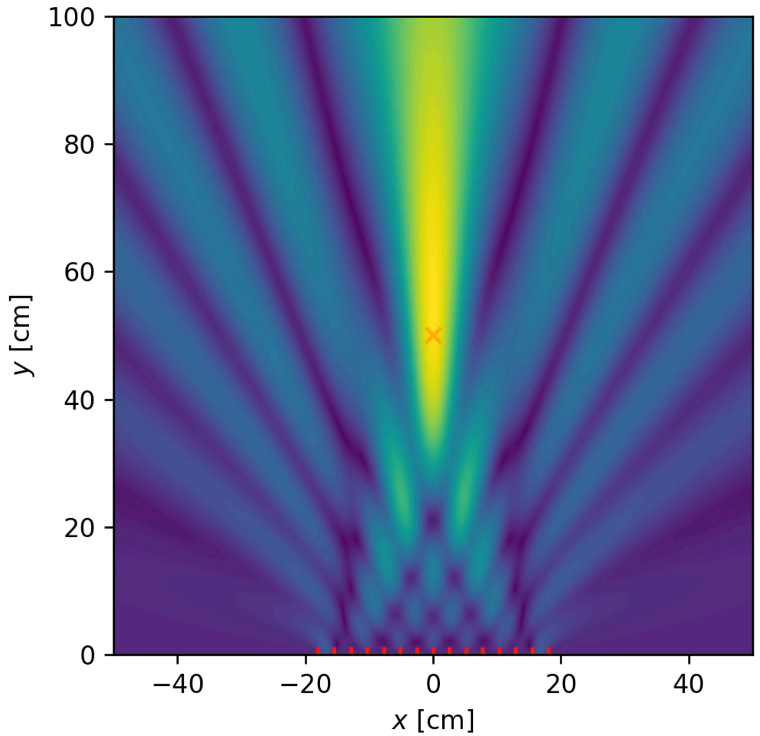

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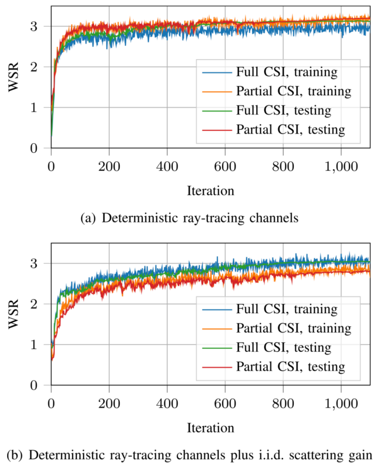
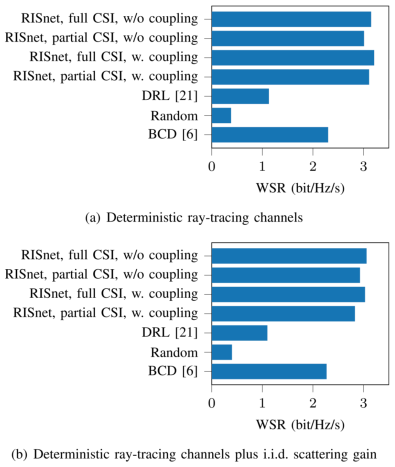
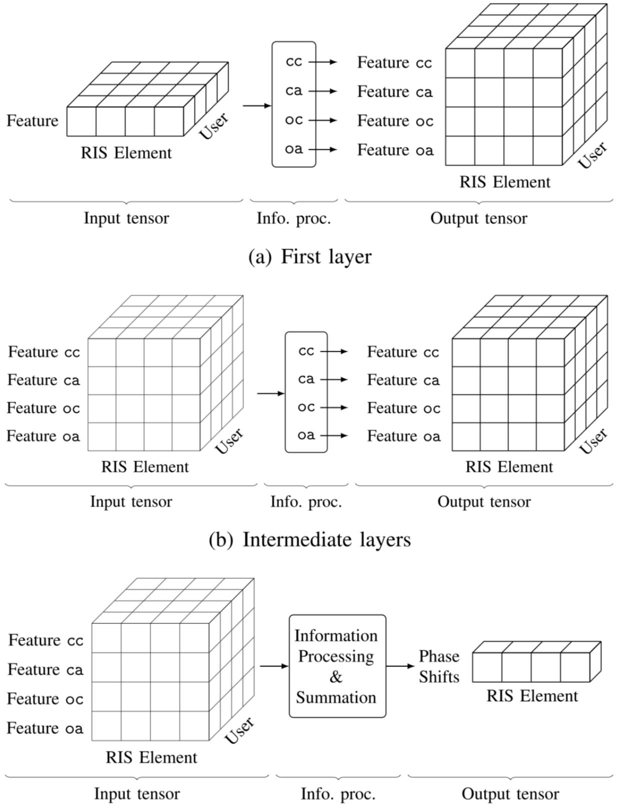
RISNet - Domain-Knowledge Driven Learning Architecture

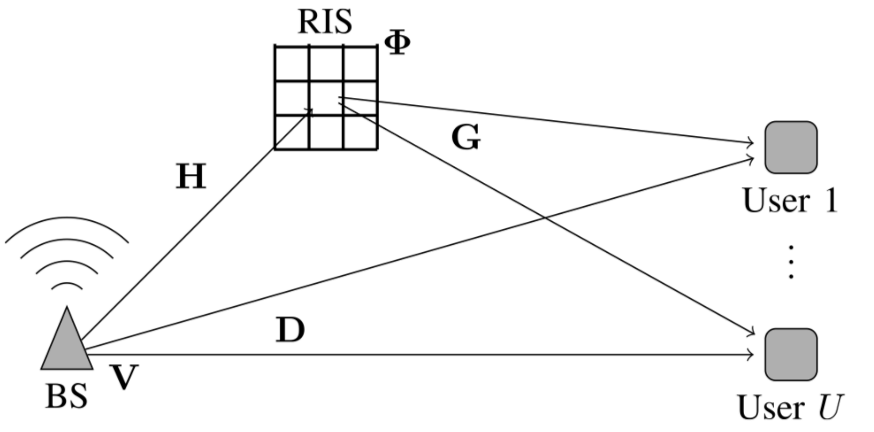
Unsupervised machine learning

$$\max_{\theta} K = \sum_{\boldsymbol{\Gamma} \in \mathcal{D}} f(\boldsymbol{\Gamma}, N_\theta(\boldsymbol{\Gamma}); \theta)$$







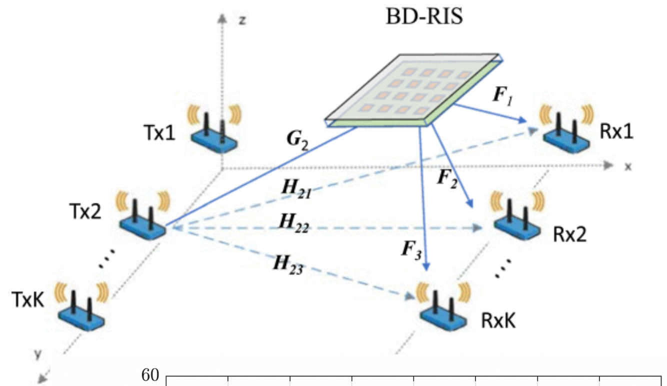


$$\max_{\mathbf{V}, \boldsymbol{\Phi}} f = \sum_{u=1}^{U} w_u \log_2 \left(1 + \frac{|l_{uu}|^2}{\sum_{v \neq u} |l_{uv}|^2 + \sigma^2}\right)$$

$$\text{s.t. } \operatorname{Tr}\left(\mathbf{V}\mathbf{V}^H\right) \leq E_{Tr},$$
$$|\phi_{nn}| = 1 \text{ for } n = 1, \ldots, N,$$
$$|\phi_{nn'}| = 0 \text{ for } n, n' = 1, \ldots, N \text{ and } n \neq n'$$

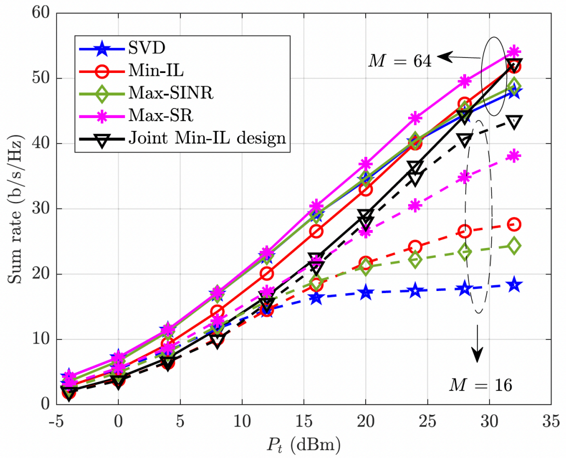
B. Peng et al., "RISnet: A Domain-Knowledge Driven Neural Network Architecture for RIS Optimization With Mutual Coupling and Partial CSI," in IEEE Transactions on Wireless Communications, vol. 24, no. 5, pp. 4469-4482, May 2025, doi: 10.1109/TWC.2025.3536178.

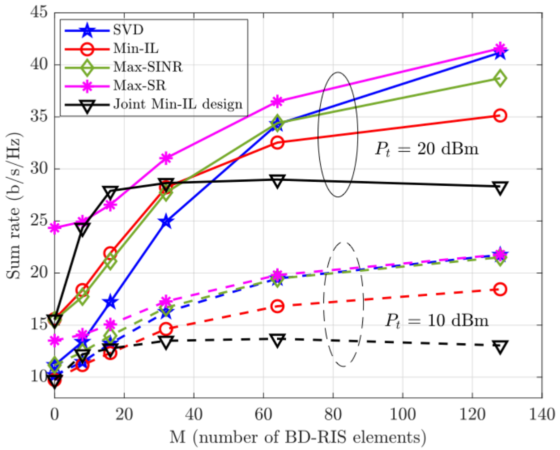
From Diagonal to Beyond-Diagonal RIS

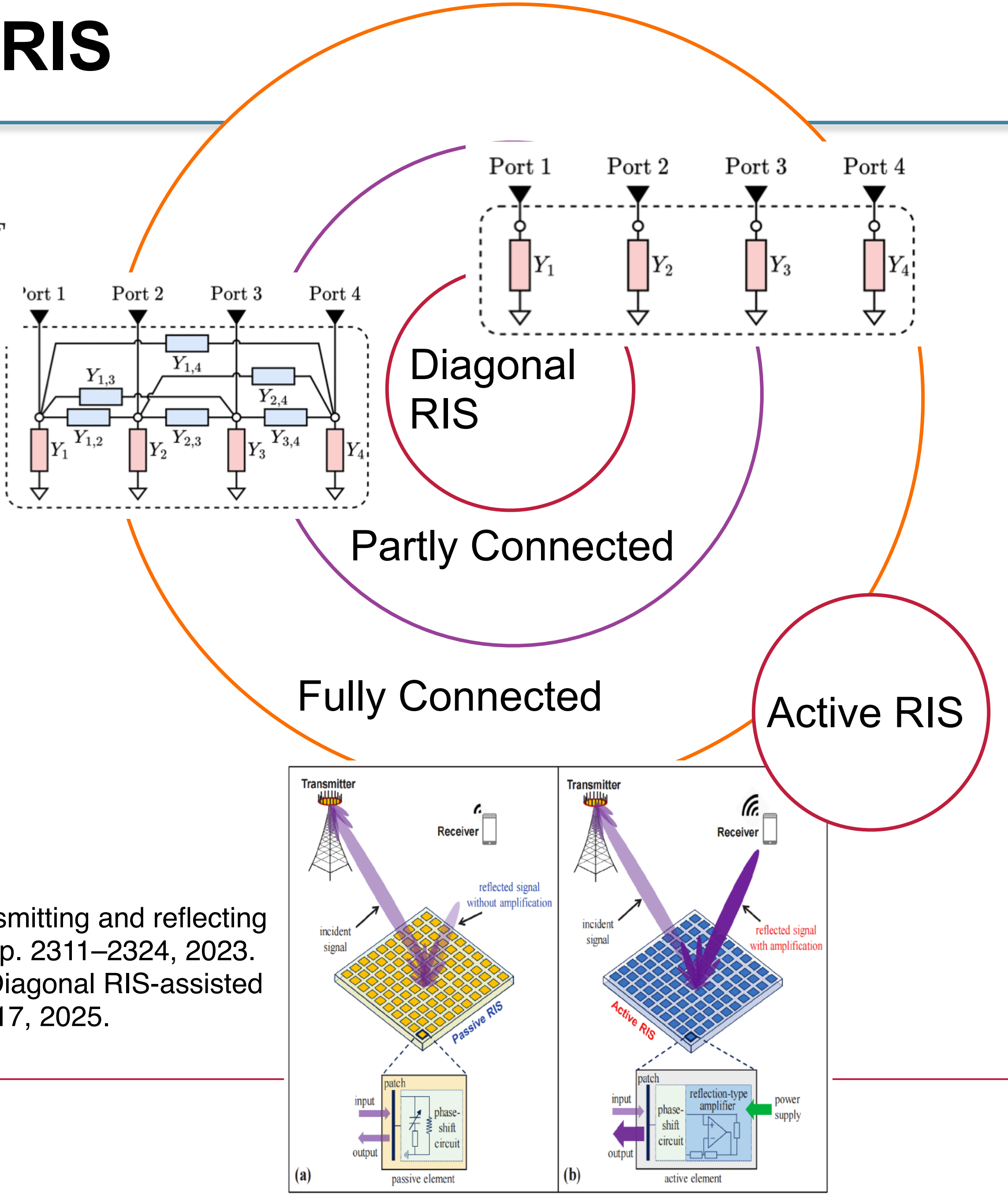


$$(\mathcal{P}_1): \min_{\boldsymbol{\Theta}} \sum_{k=1}^{K} \sum_{l=1, l\neq k}^{K} \|\mathbf{H}_{lk} + \mathbf{F}_k \boldsymbol{\Theta} \mathbf{G}_l^H\|_F^2$$
$$\text{s.t. } \boldsymbol{\Theta}^T = \boldsymbol{\Theta},\ \boldsymbol{\Theta}^H \boldsymbol{\Theta} = \mathbf{I}_M.$$

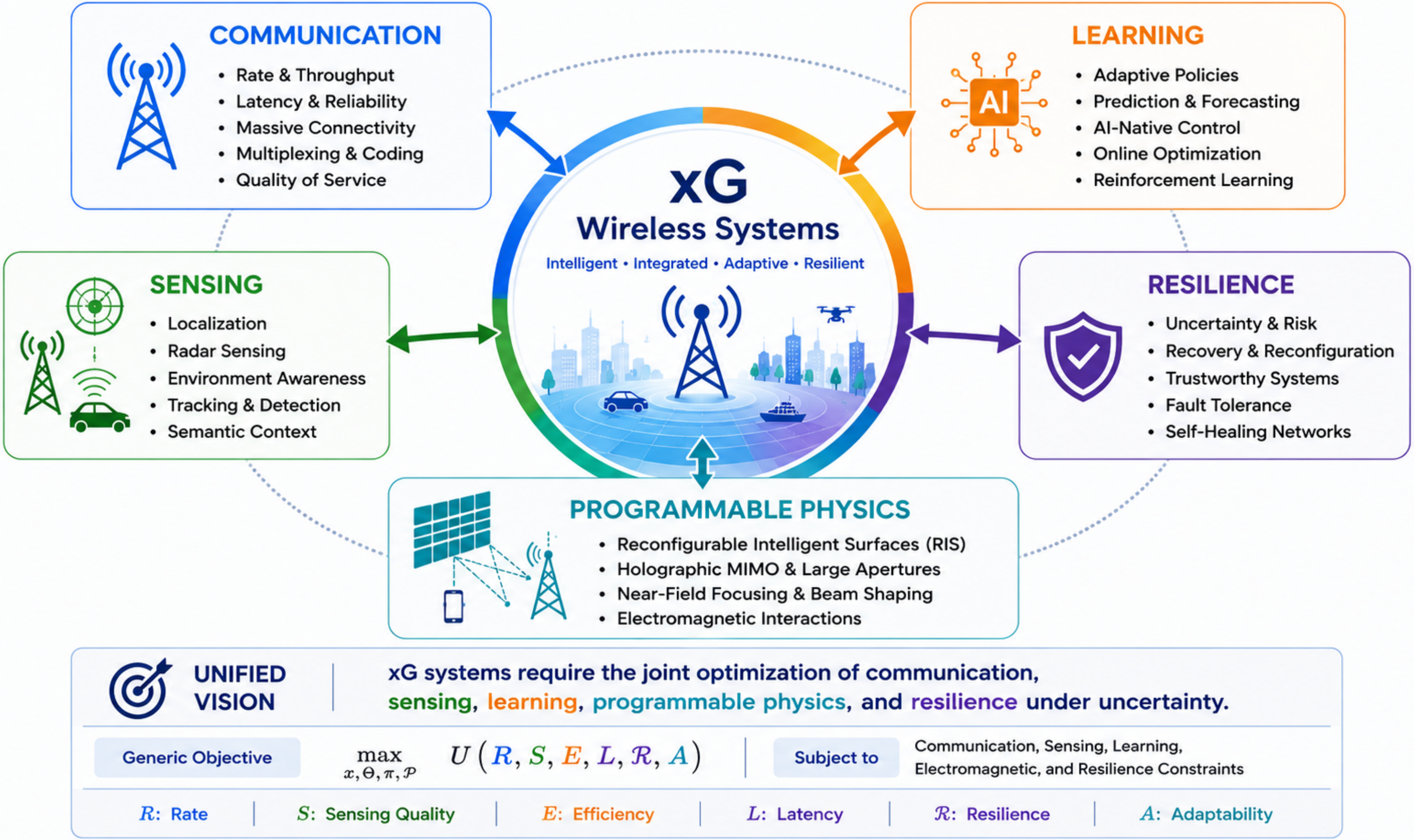
Takagi-Factorization







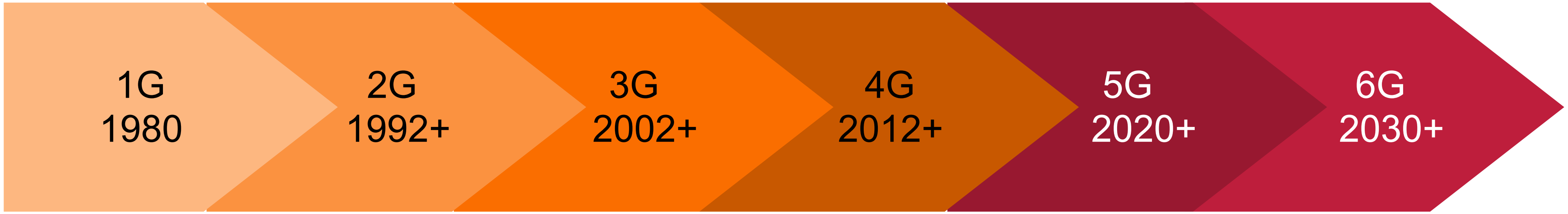
- H. Li, S. Shen, and B. Clerckx, “Beyond diagonal reconfigurable intelligent surfaces: From transmitting and reflecting modes to single-, group-, and fully-connected architectures,” IEEE Trans. Wire. Com., vol. 22, pp. 2311–2324, 2023.
- I. Santamaria, M. Soleymani, E. Jorswieck, J. Gutiérrez, "Interference Minimization in Beyond-Diagonal RIS-assisted MIMO Interference Channels", IEEE Open Journal of Vehicular Technology, vol. 6, pp. 1005-1017, 2025.


COMMUNICATION
Rate & Throughput
Latency & Reliability
Massive Connectivity
Multiplexing & Coding
Quality of Service
LEARNING
AI
Adaptive Policies
Prediction & Forecasting
AI-Native Control
Online Optimization
Reinforcement Learning
xG
Wireless Systems
Intelligent • Integrated • Adaptive • Resilient
SENSING
Localization
Radar Sensing
Environment Awareness
Tracking & Detection
Semantic Context
RESILIENCE
Uncertainty & Risk
Recovery & Reconfiguration
Trustworthy Systems
Fault Tolerance
Self-Healing Networks
PROGRAMMABLE PHYSICS
Reconfigurable Intelligent Surfaces (RIS)
Holographic MIMO & Large Apertures
Near-Field Focusing & Beam Shaping
Electromagnetic Interactions
UNIFIED VISION
xG systems require the joint optimization of communication, sensing, learning, programmable physics, and resilience under uncertainty.
Generic Objective
$\max_{x,\Theta,\pi,\mathcal{P}} U(R, S, E, L, \mathcal{R}, A)$
Subject to
Communication, Sensing, Learning, Electromagnetic, and Resilience Constraints
R: Rate
S: Sensing Quality
E: Efficiency
L: Latency
$\mathcal{R}$: Resilience
A: Adaptability

Conclusions and Future Works

- **Four eras** identified and connected to corresponding optimization problems
  - Era I - MIMO and Multiuser Systems - matrix optimization, rate region boundaries
  - Era II - Interference Networks - distributed optimization, conflict, equilibria
  - Era III - Beyond Throughput - energy, security, robustness, combinations
  - Era IV - Toward xG -

- Growing programming problem - multi-objectives, constraints, uncertainty, opt. parameters



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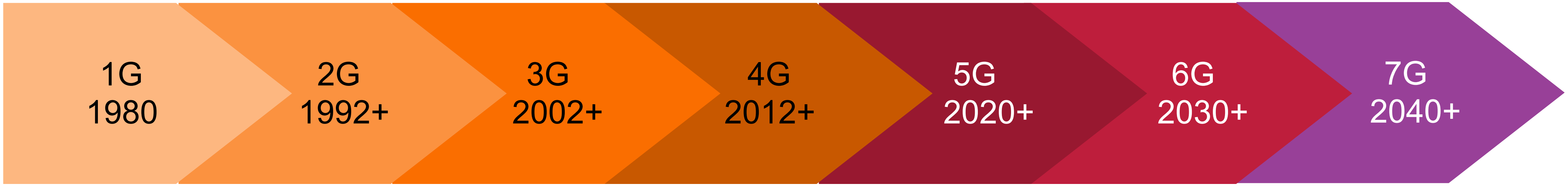

Quantum