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Wireless 2.0

Marco Di Renzo

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Wireless 2.0:
Towards Smart Radio Environments Empowered by Reconfigurable Intelligent Metasurfaces and AI

Marco Di Renzo

Paris-Saclay University
Laboratory of Signals and Systems (L2S)
CNRS and CentraleSupelec
Paris, France
marco.direnzo@centralesupelec.fr

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ITU AI/ML in 5G Challenge
28 September 2020 - Online

Wireless 2.0: Wireless Empowered by AI Metasurfaces

Di Renzo *et al. EURASIP Journal on Wireless Communications and Networking* (2019) 2019:129
https://doi.org/10.1186/s13638-019-1438-9

EURASIP Journal on Wireless Communications and Networking

REVIEW **Open Access**

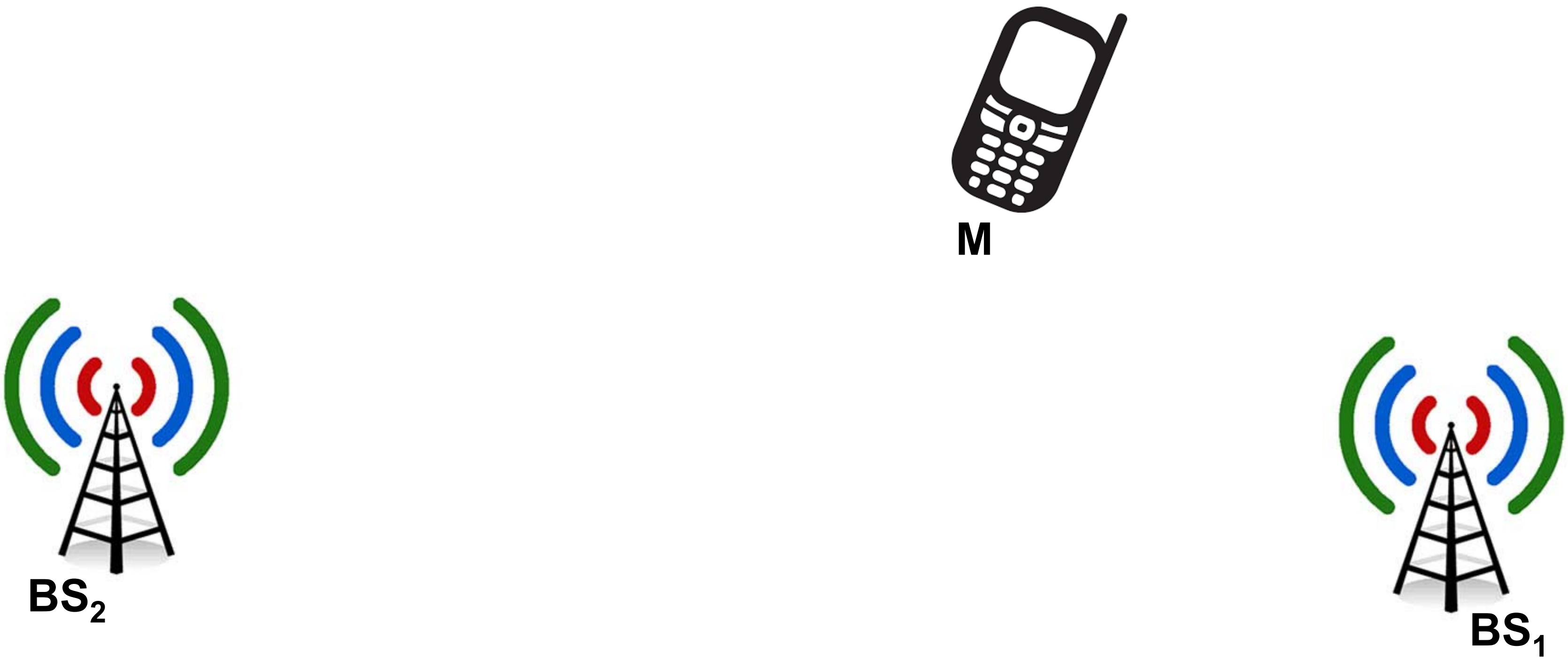
Smart radio environments empowered by reconfigurable AI meta-surfaces: an idea whose time has come

Marco Di Renzo[1*], Merouane Debbah[2], Dinh-Thuy Phan-Huy[3], Alessio Zappone[4], Mohamed-Slim Alouini[5], Chau Yuen[6], Vincenzo Sciancalepore[7], George C. Alexandropoulos[8], Jakob Hoydis[9], Haris Gacanin[10], Julien de Rosny, Ahcene Bounceur[12], Geoffroy Lerosey[13] and Mathias Fink[11]

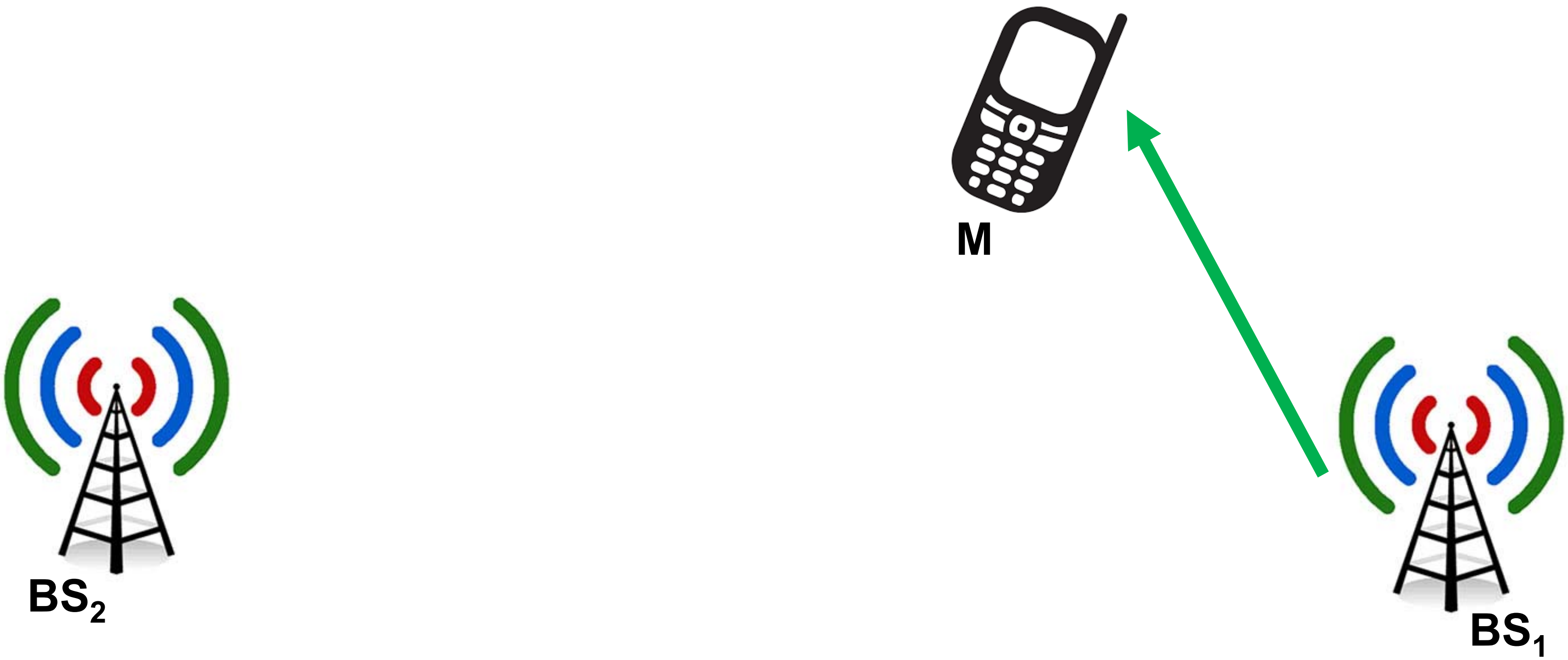
Abstract

Future wireless networks are expected to constitute a distributed intelligent wireless communications, sensing, and computing platform, which will have the challenging requirement of interconnecting the physical and digital worlds in a seamless and sustainable manner. Currently, two main factors prevent wireless network operators from building such networks: (1) the lack of control of the wireless environment, whose impact on the radio waves cannot be customized, and (2) the current operation of wireless radios, which consume a lot of power because new signals are generated whenever data has to be transmitted. In this paper, we challenge the usual "more data needs more power and emission of radio waves" status quo, and motivate that future wireless networks necessitate a smart radio environment: a transformative wireless concept, where the environmental objects are coated with artificial thin films of electromagnetic and reconfigurable material (that are referred to as reconfigurable intelligent meta-surfaces), which are capable of sensing the environment and of applying customized transformations to the radio waves. Smart radio environments have the potential to provide future wireless networks with uninterrupted wireless connectivity,

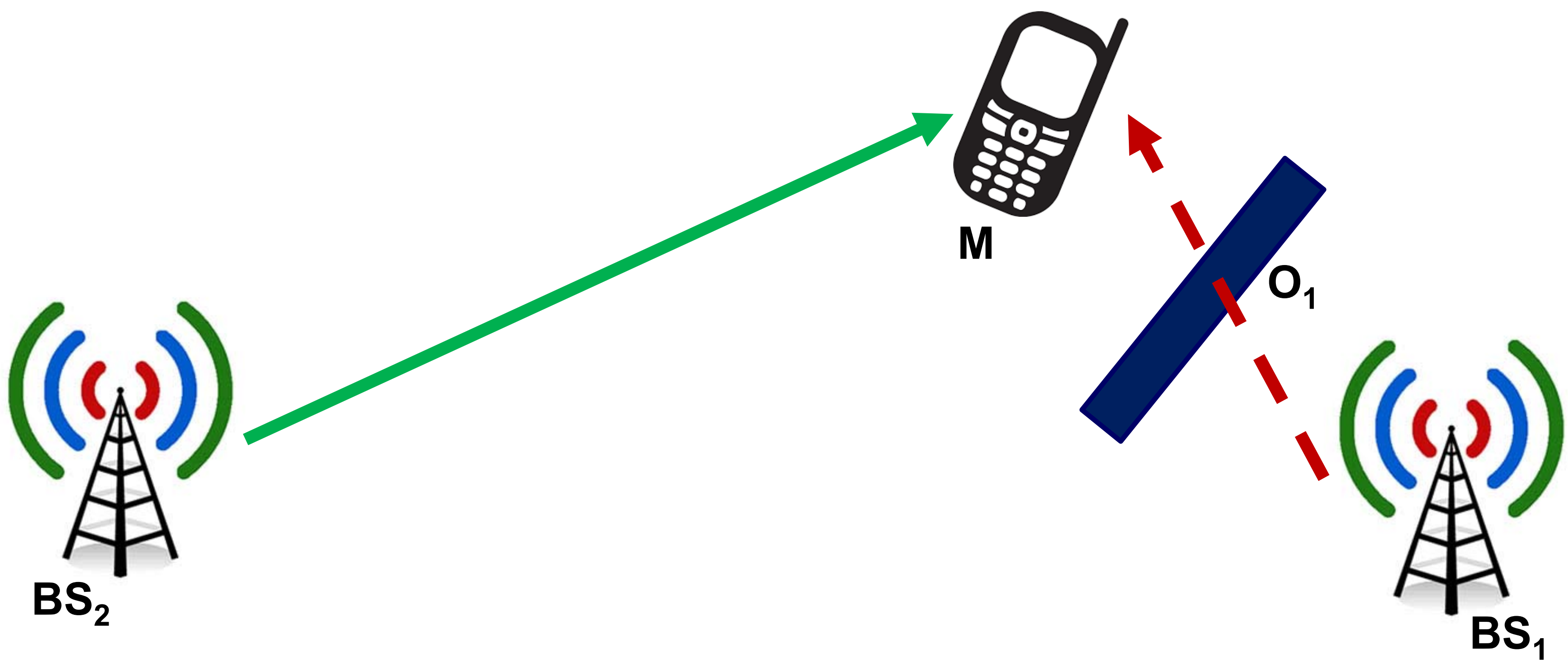
Current Wireless Networks



Current Wireless Networks



Current Wireless Networks



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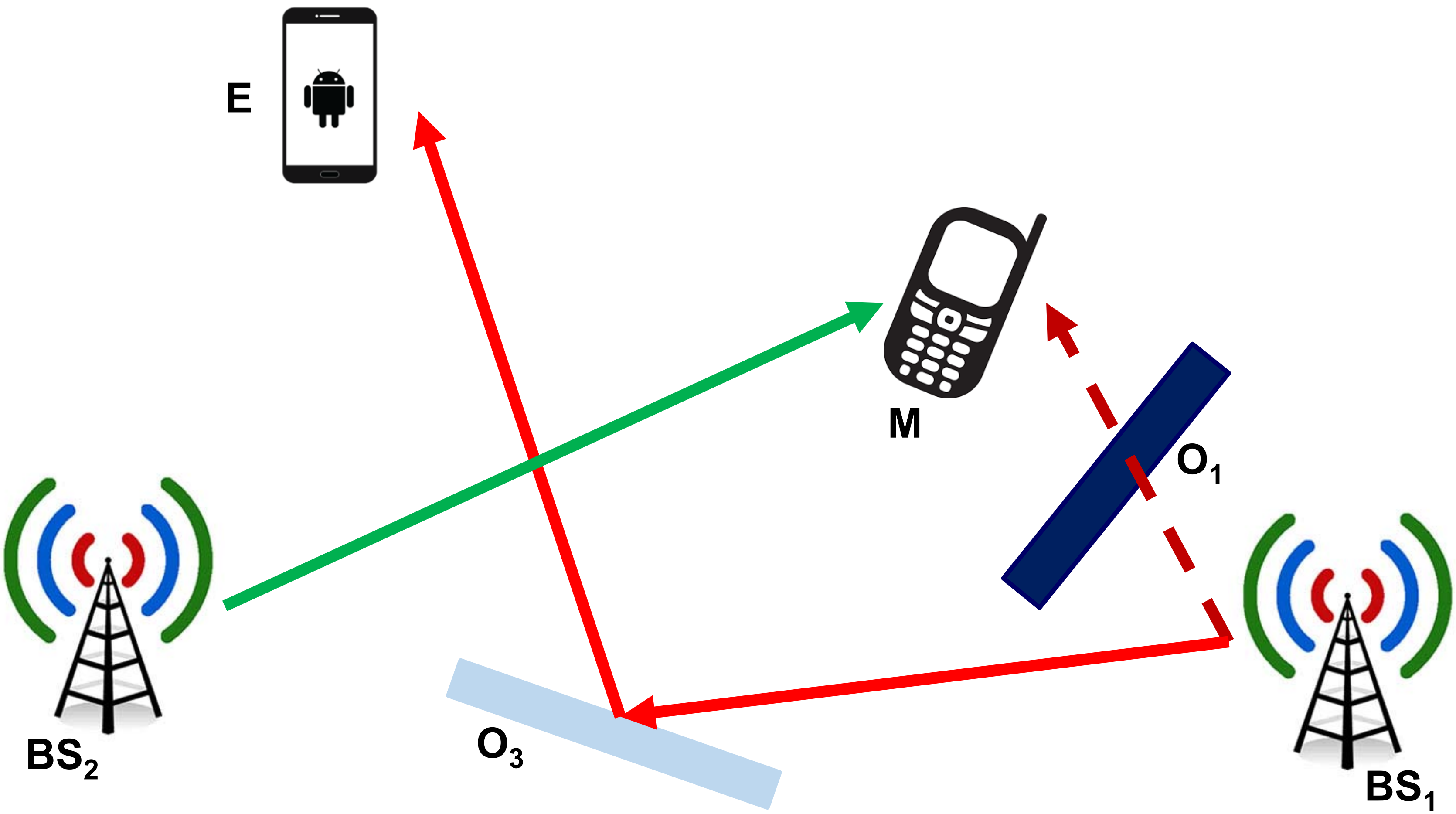
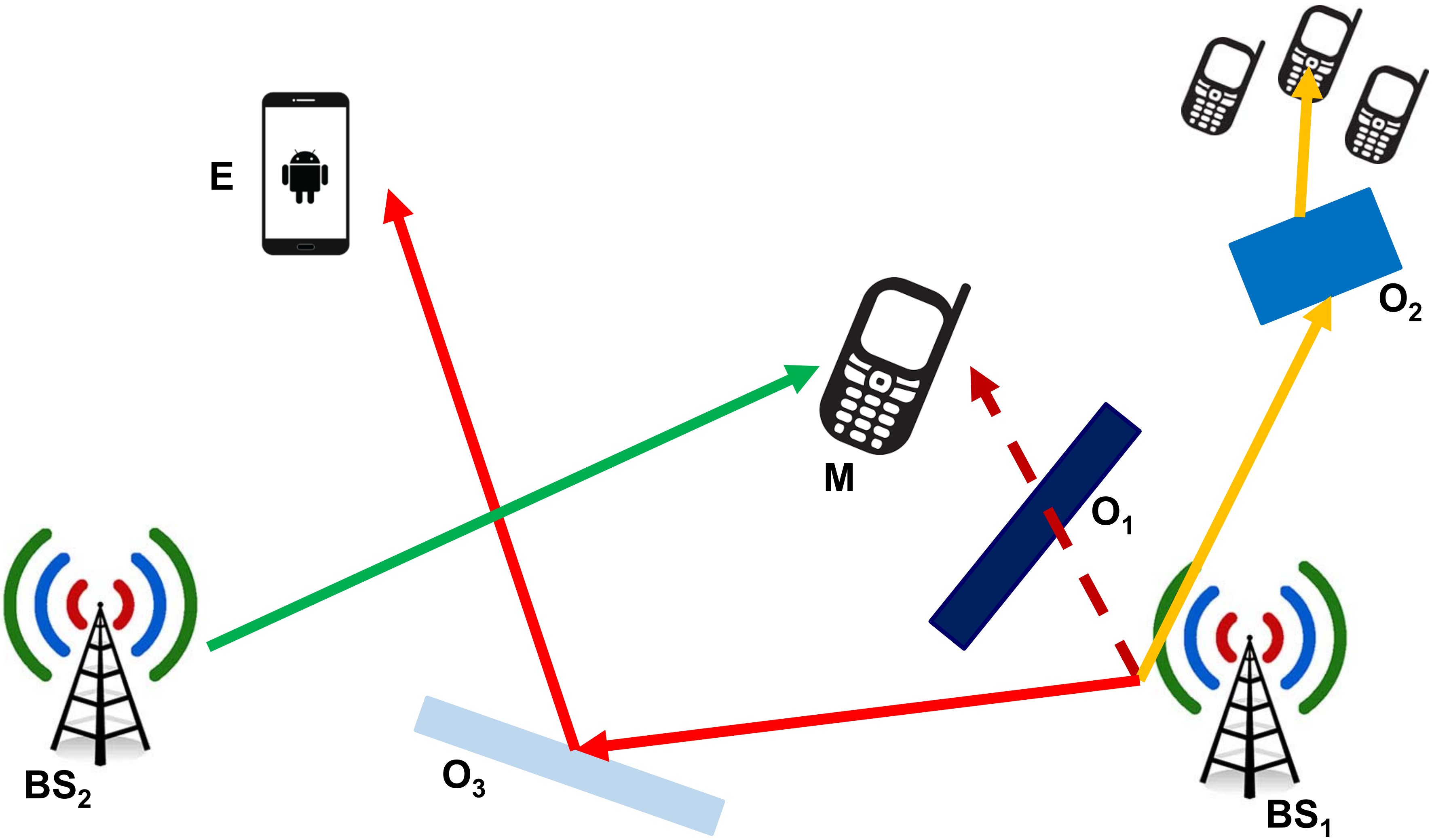
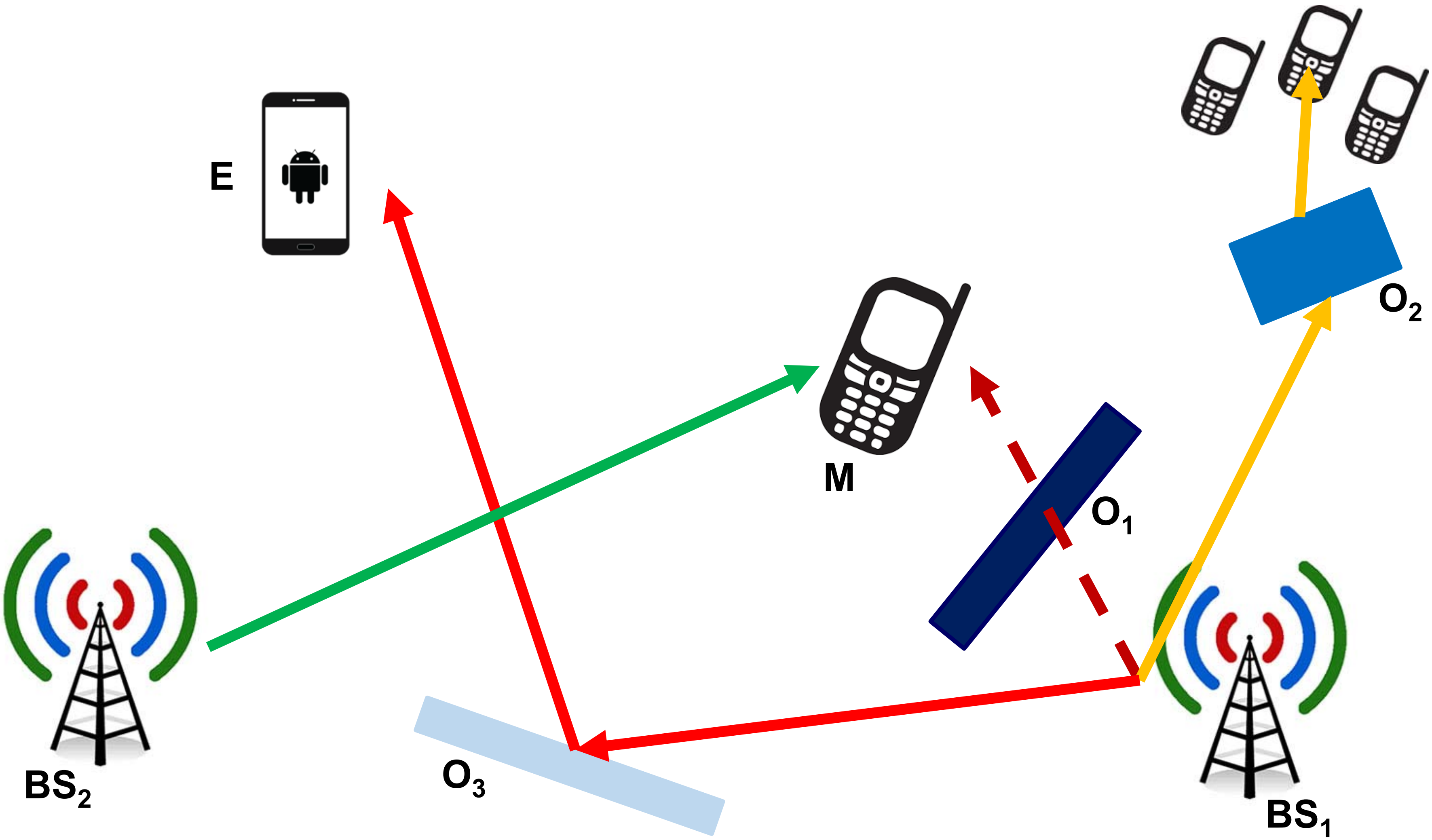


Current Wireless Networks



Current Wireless Networks: No Control of Radio Waves



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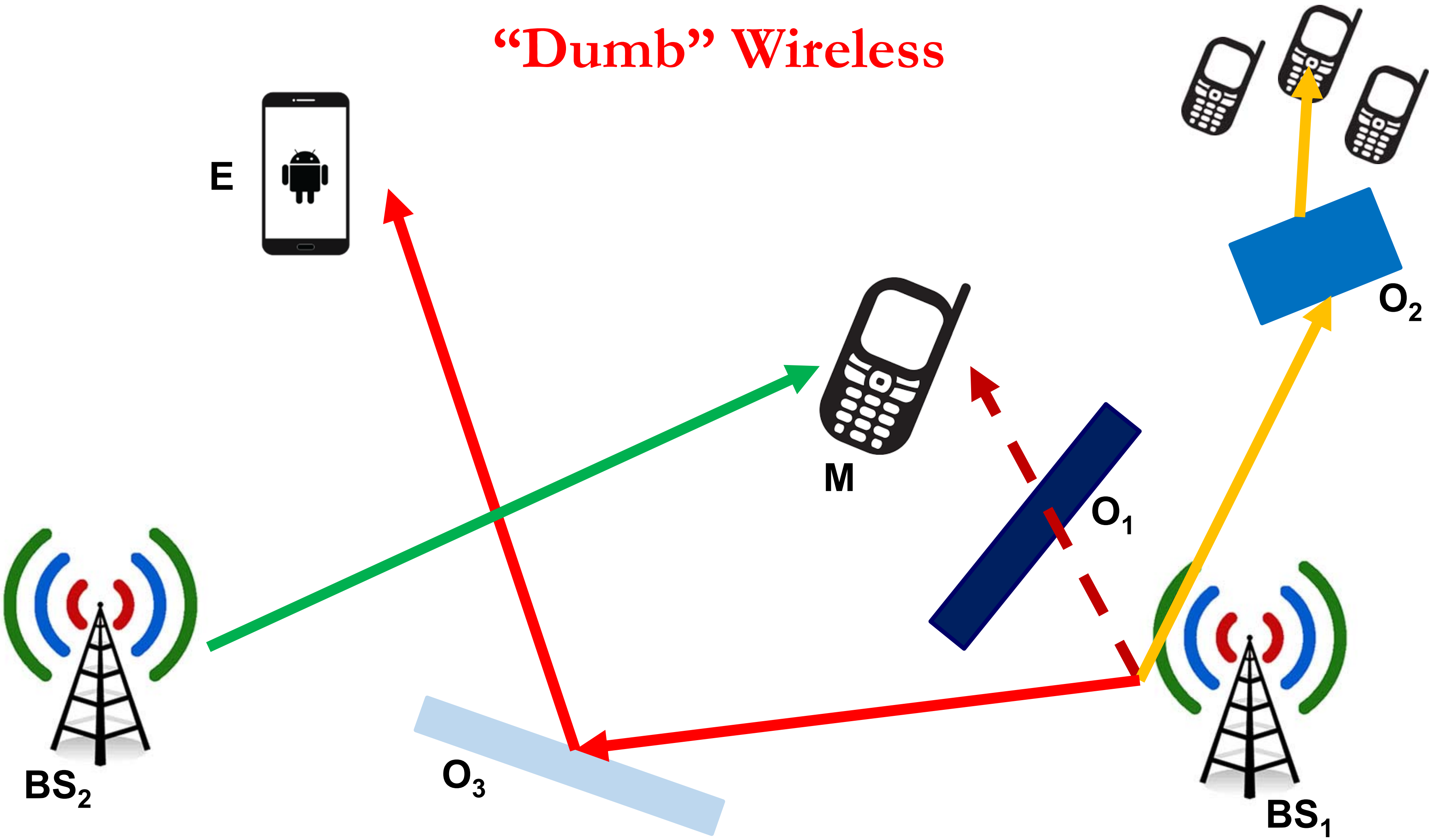

Current Wireless Networks: No Control of Radio Waves

- **In conventional networks:**

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  - **We usually perceive the environment as an "unintentional adversary" to communication**

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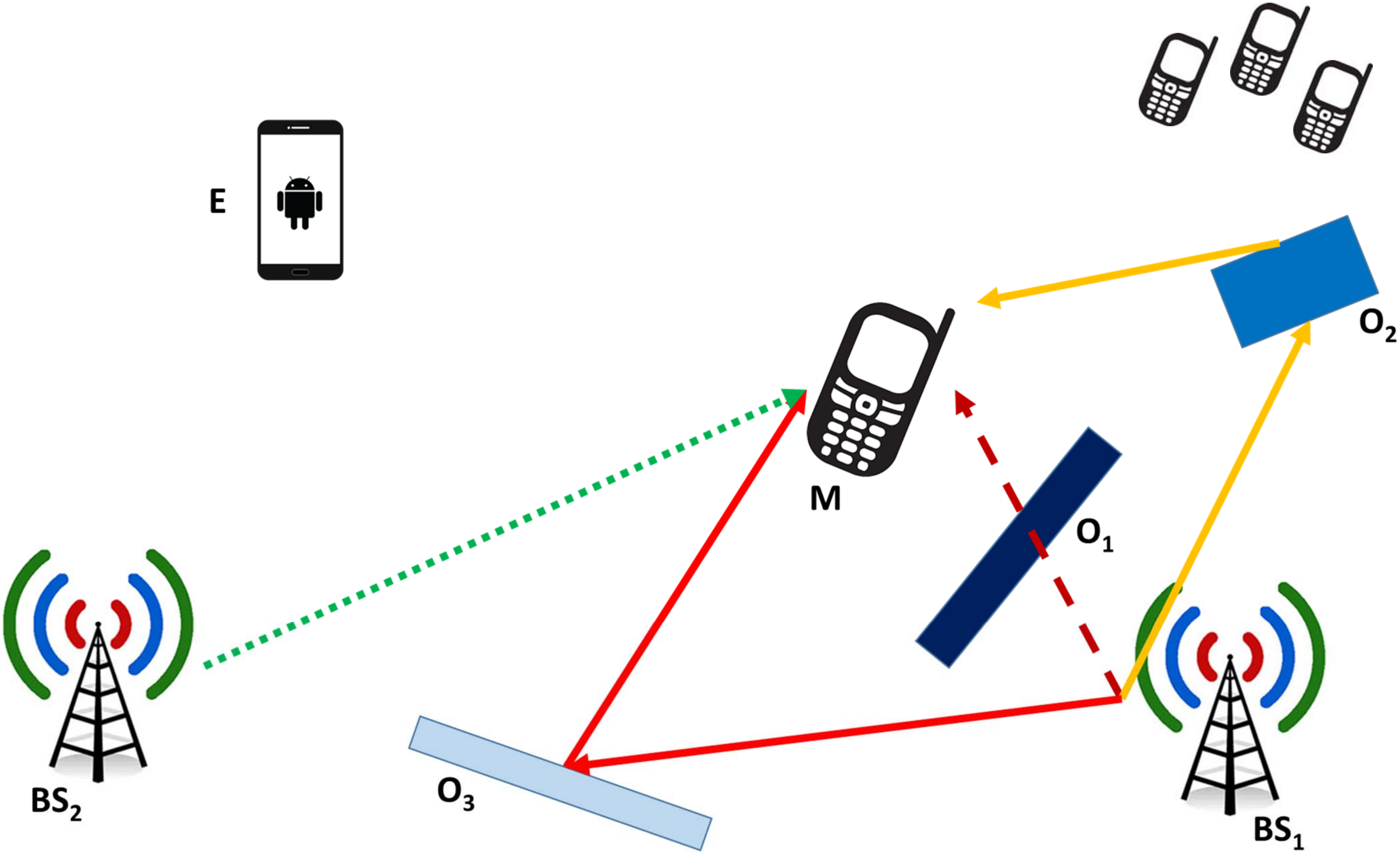
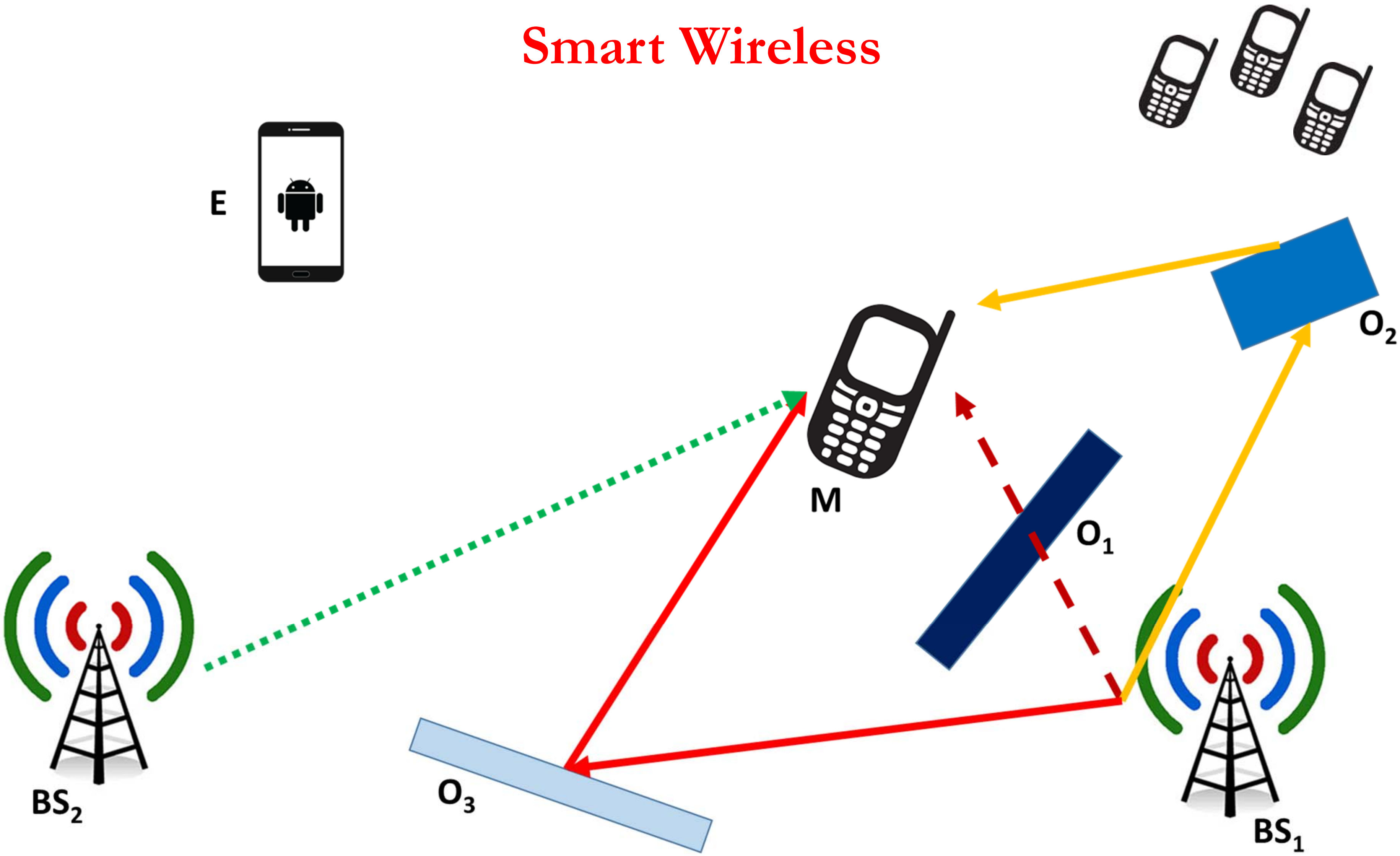
… WHAT IF …

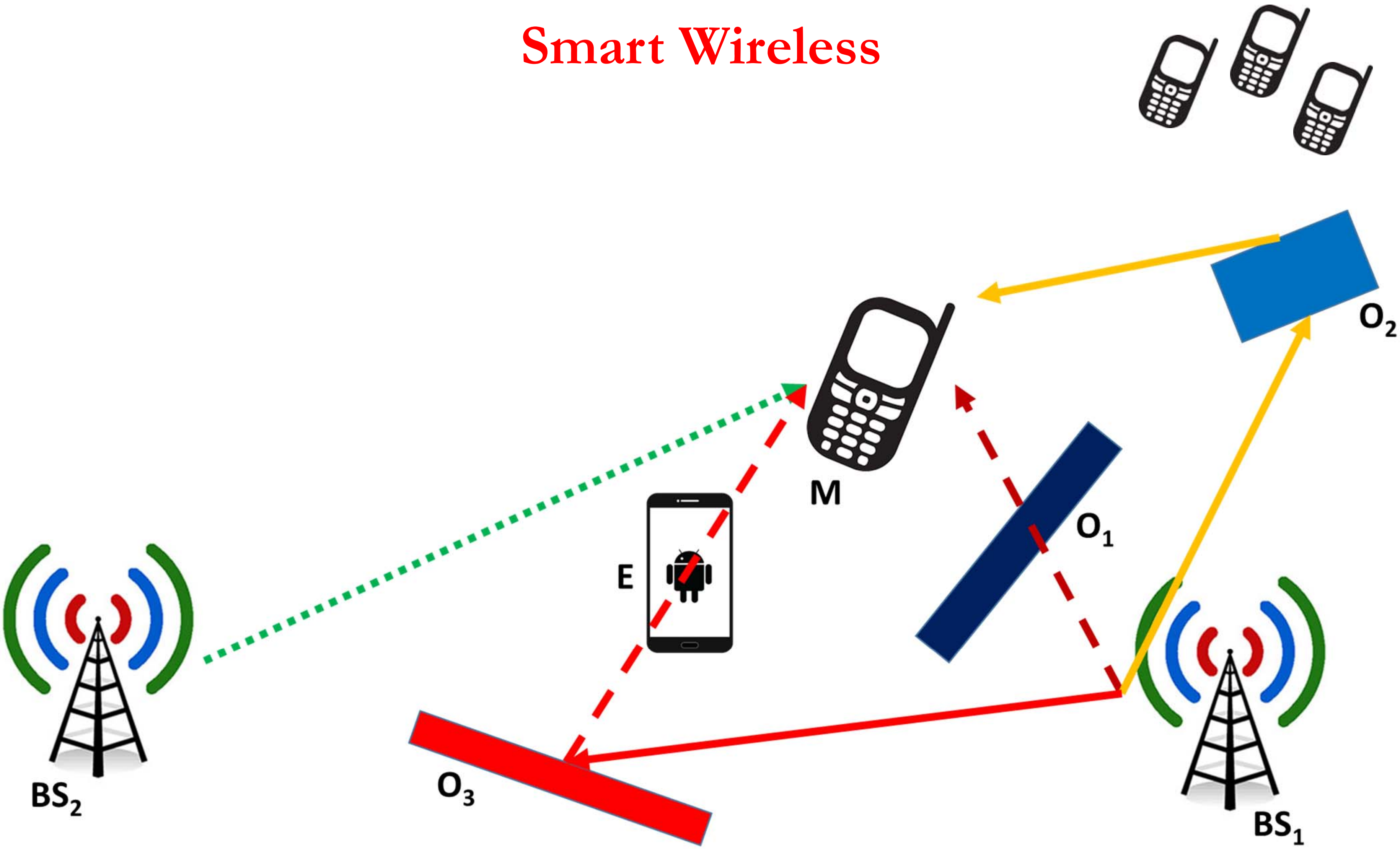
Smart Radio Environments



Smart Wireless



Smart Wireless



Smart Wireless

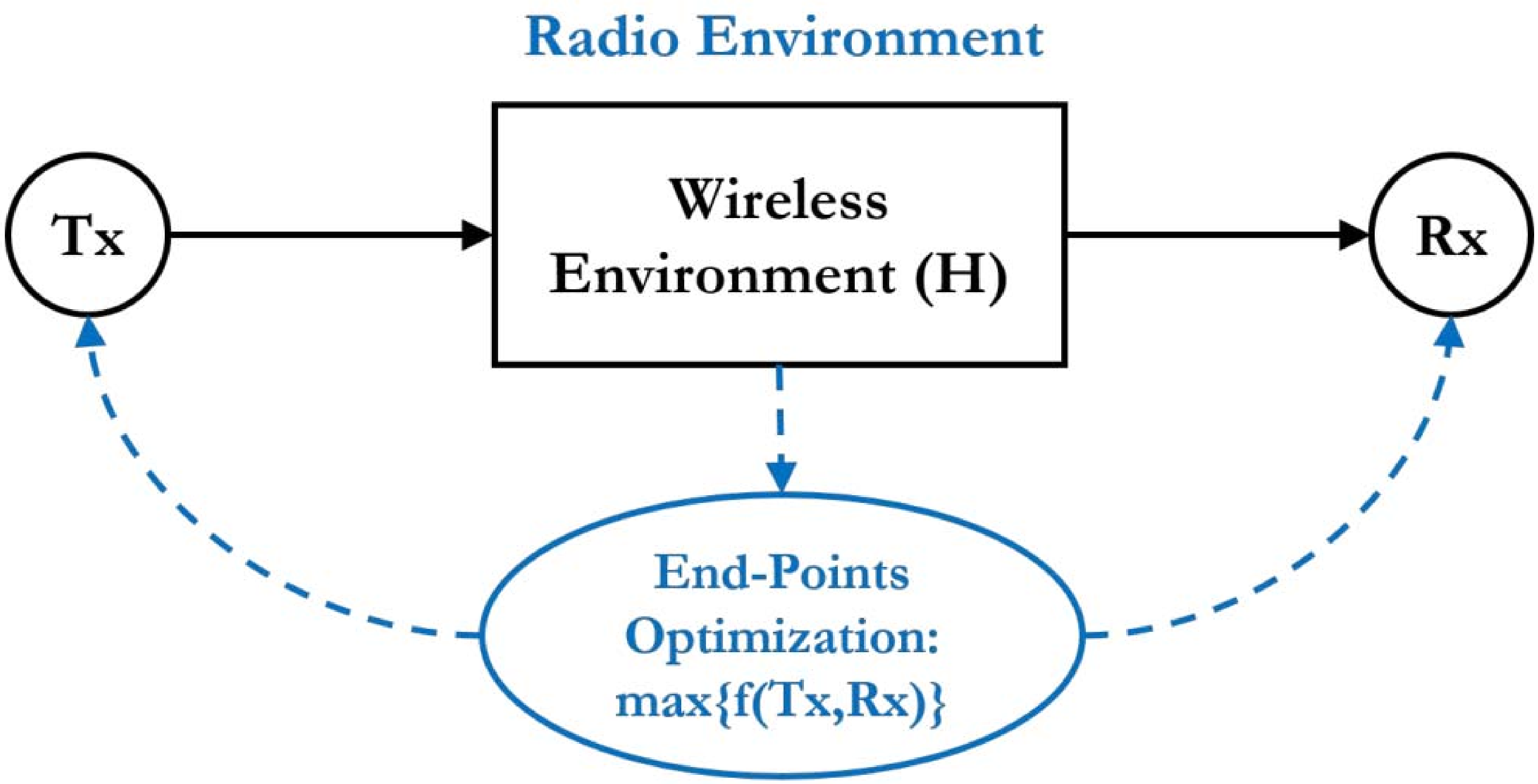
… from <u>adaptation</u> to …

Control & Programmability

Radio Environments

Adaptation: End-Points Optimization

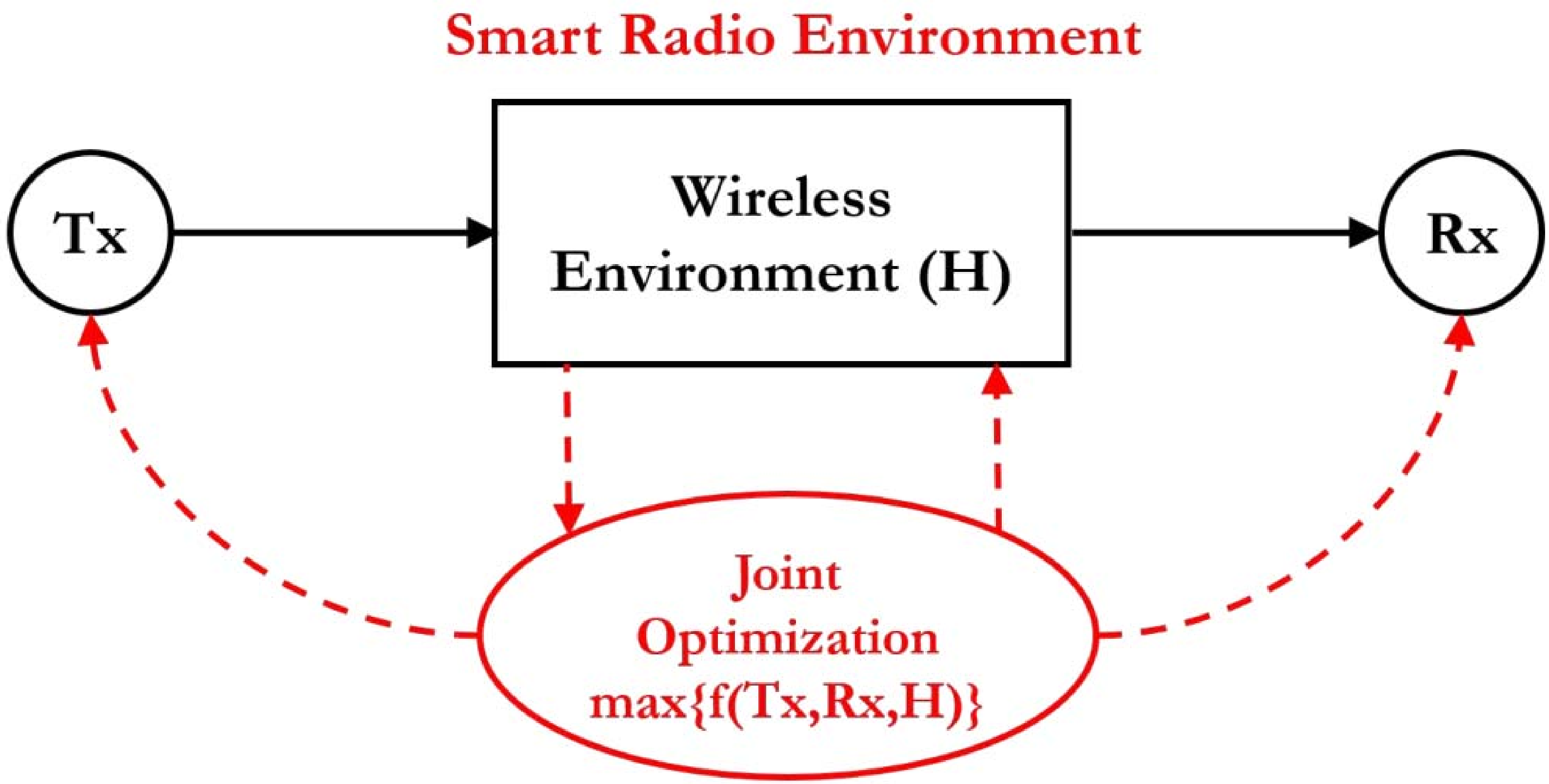
Adaptation: End-Points Optimization



Smart Radio Environments

Control & Programmability: Joint Optimization

Control & Programmability: Joint Optimization



Smart Wireless

… from adaptation to …

Control & Programmability

Smart Wireless

… from <u>adaptation</u> to …

Control & Programmability

↓

Technology

Smart Wireless

… from <u>adaptation</u> to …

Control & Programmability

↓

Technology

↓

RIS (metasurface)

Smart Wireless

… from <u>adaptation</u> to …

Control & Programmability

↓ Algorithms

↓ Technology

↓ RIS (metasurface)

Smart Wireless

… from <u>adaptation</u> to …

Control & Programmability

↓ Algorithms ↓ ML/AI

↓ Technology ↓ RIS (metasurface)

The Technology: Reconfigurable Intelligent Surface

The Technology: Reconfigurable Intelligent Surface

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Press Release

January 17, 2020

DOCOMO Conducts World's First Successful Trial of Transparent Dynamic Metasurface

— Dynamic wave manipulation and high transparency expected to optimize 5G network construction —

Print Like Tweet

TOKYO, JAPAN, January 17, 2020 --- NTT DOCOMO, INC., working in collaboration with the global glass

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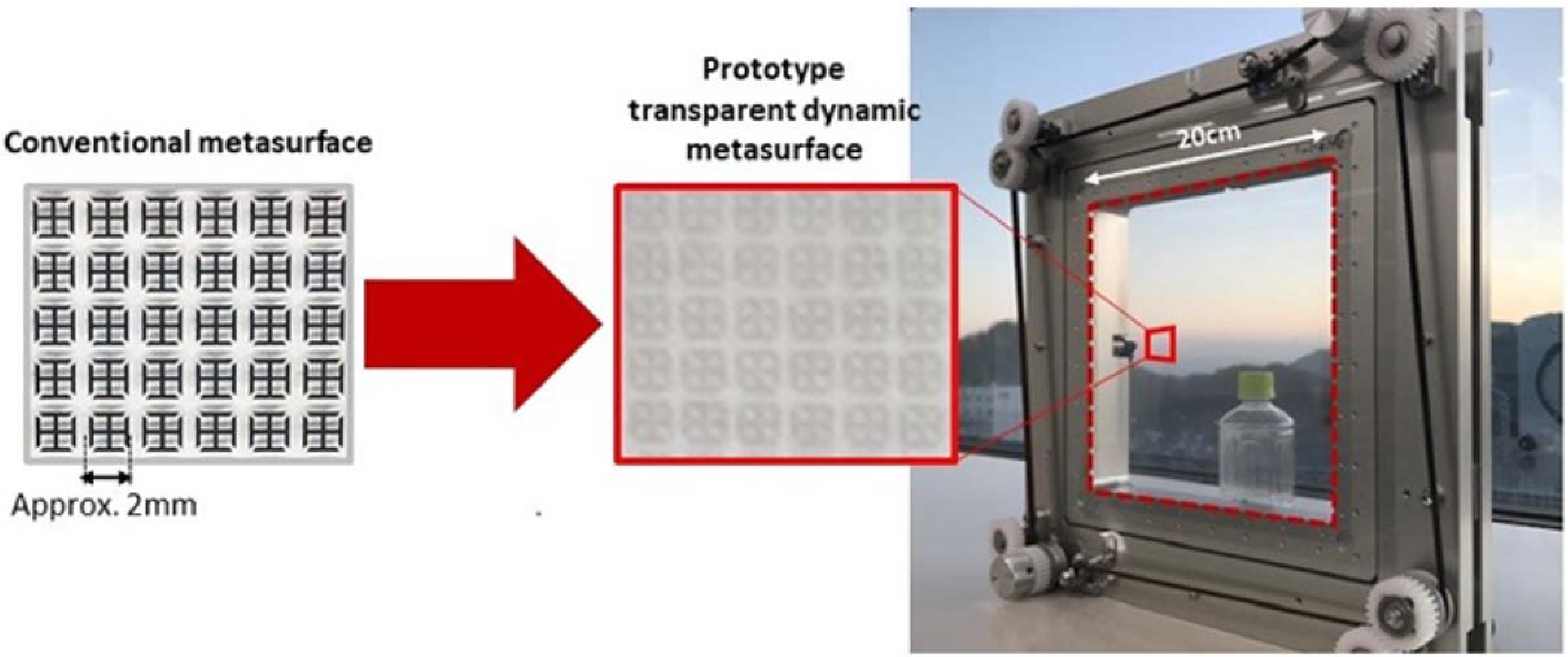
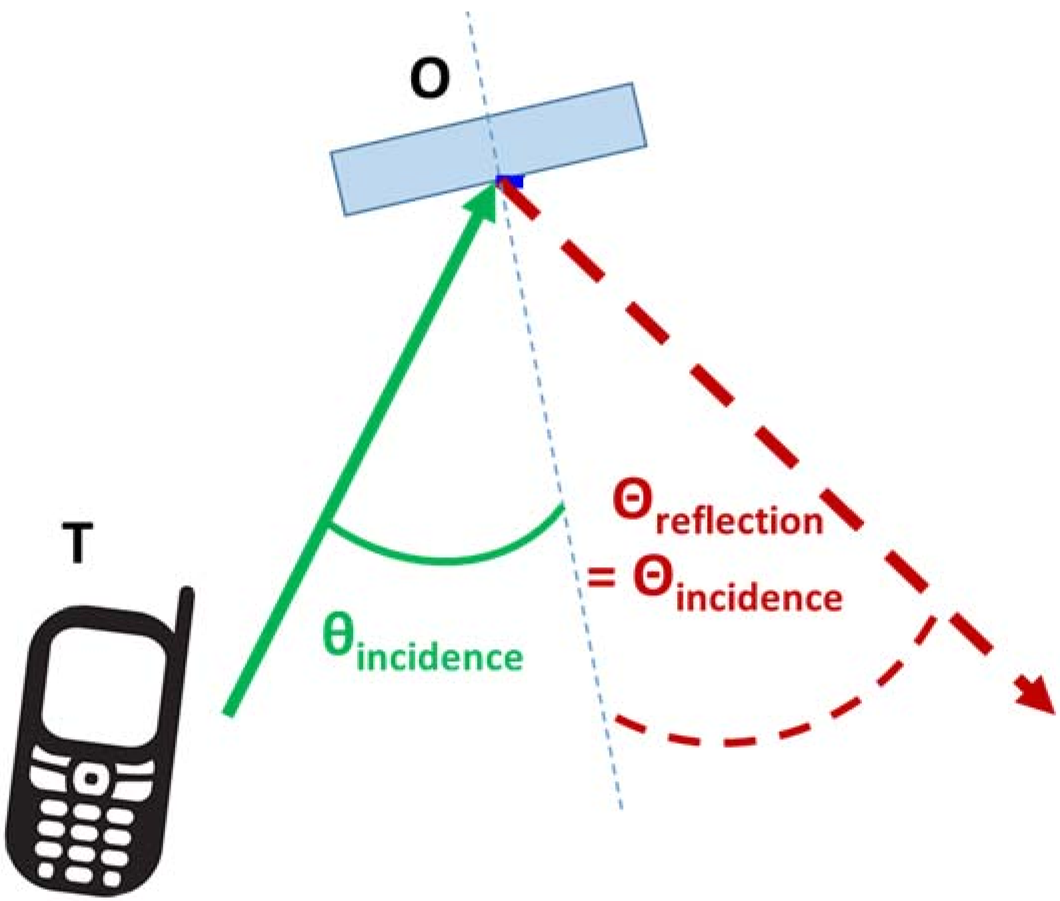
Metasurface-Based RIS
(transparent and dynamic, Jan. 2020)



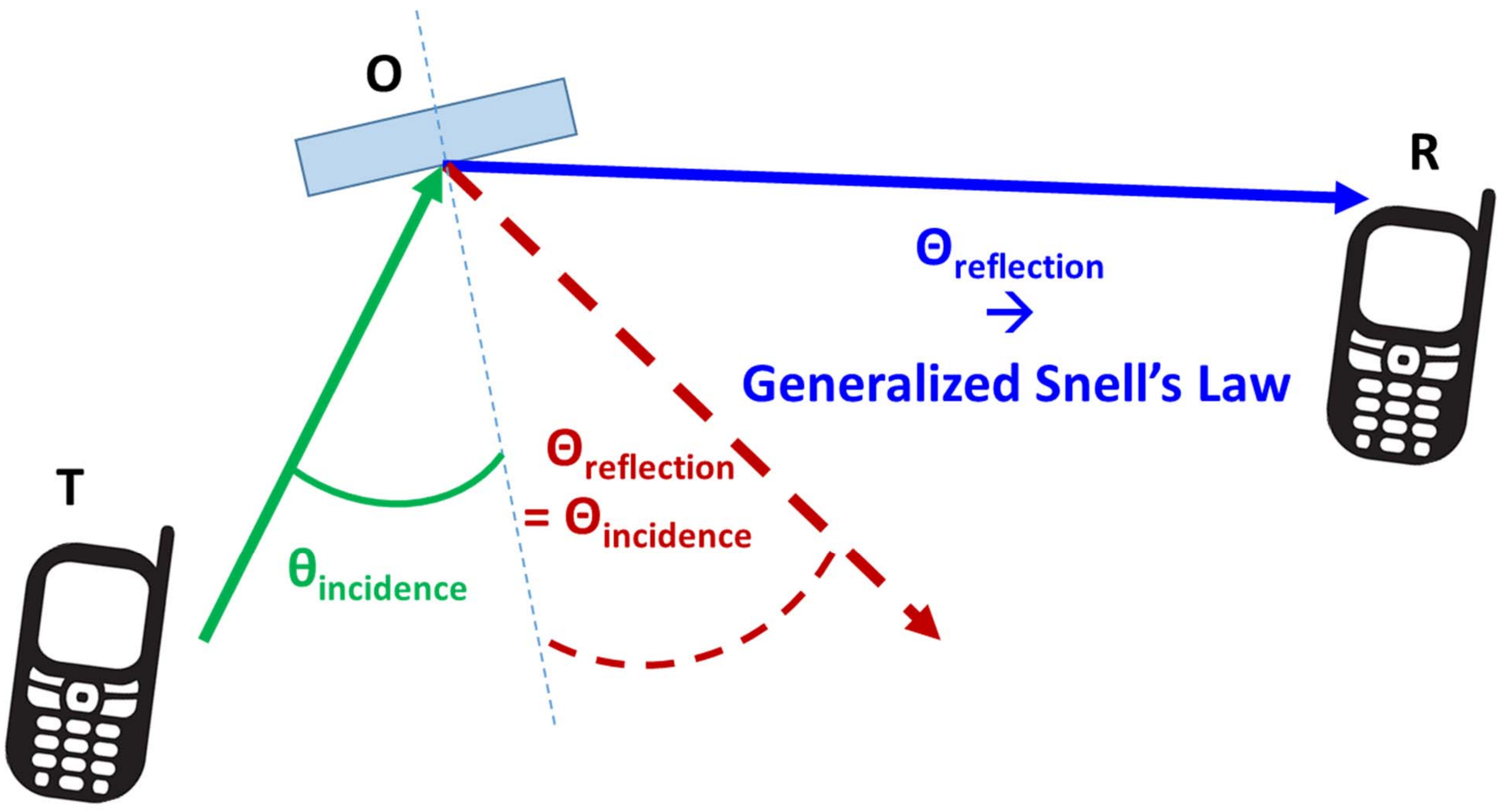
Prototype of transparent dynamic metasurface

The Technology: Reconfigurable Intelligent Surface

From Reflections …



… to Smart Reflections



The Technology: Reconfigurable Intelligent Surface

The Brain & Algorithms: Artificial Intelligence

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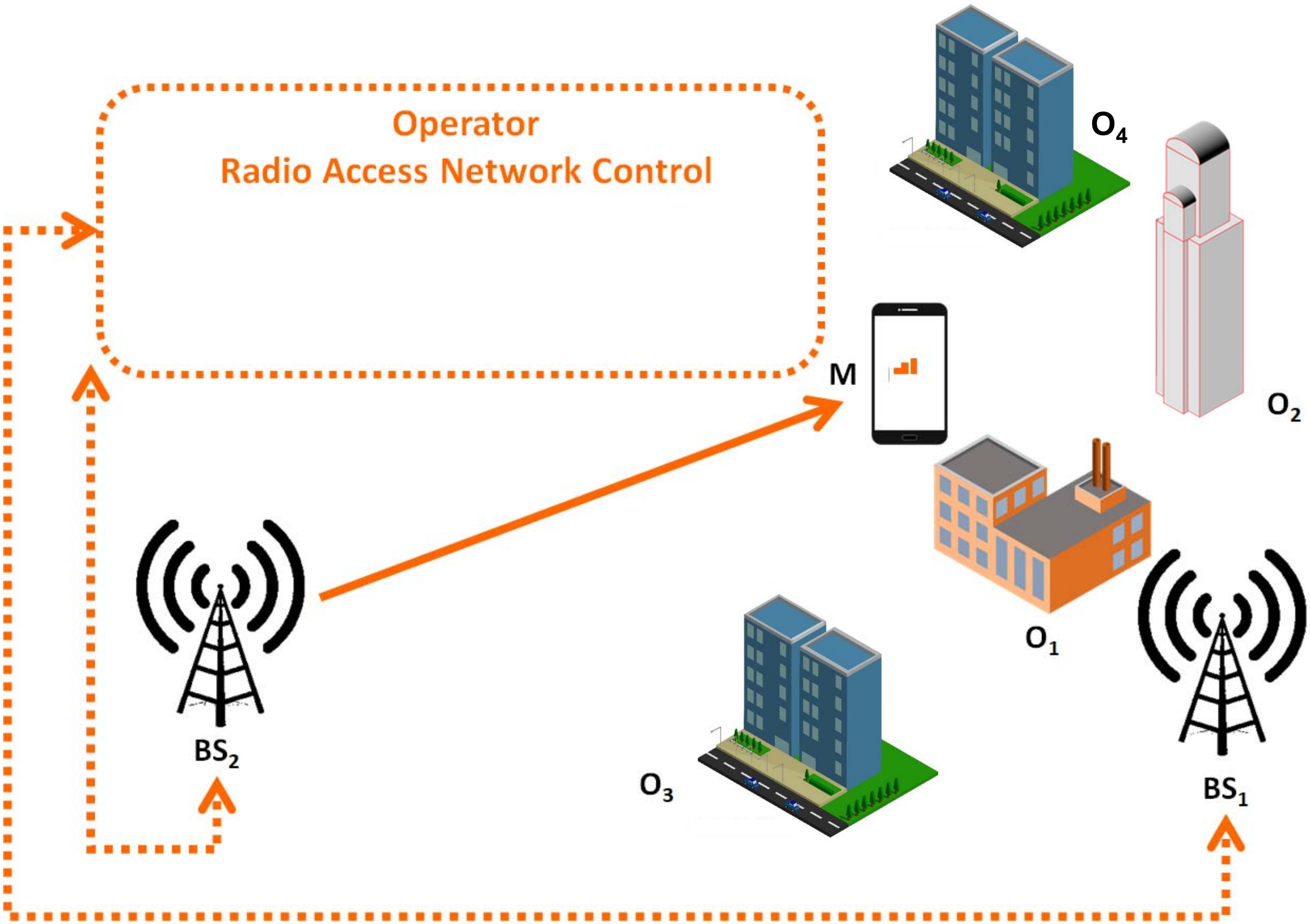
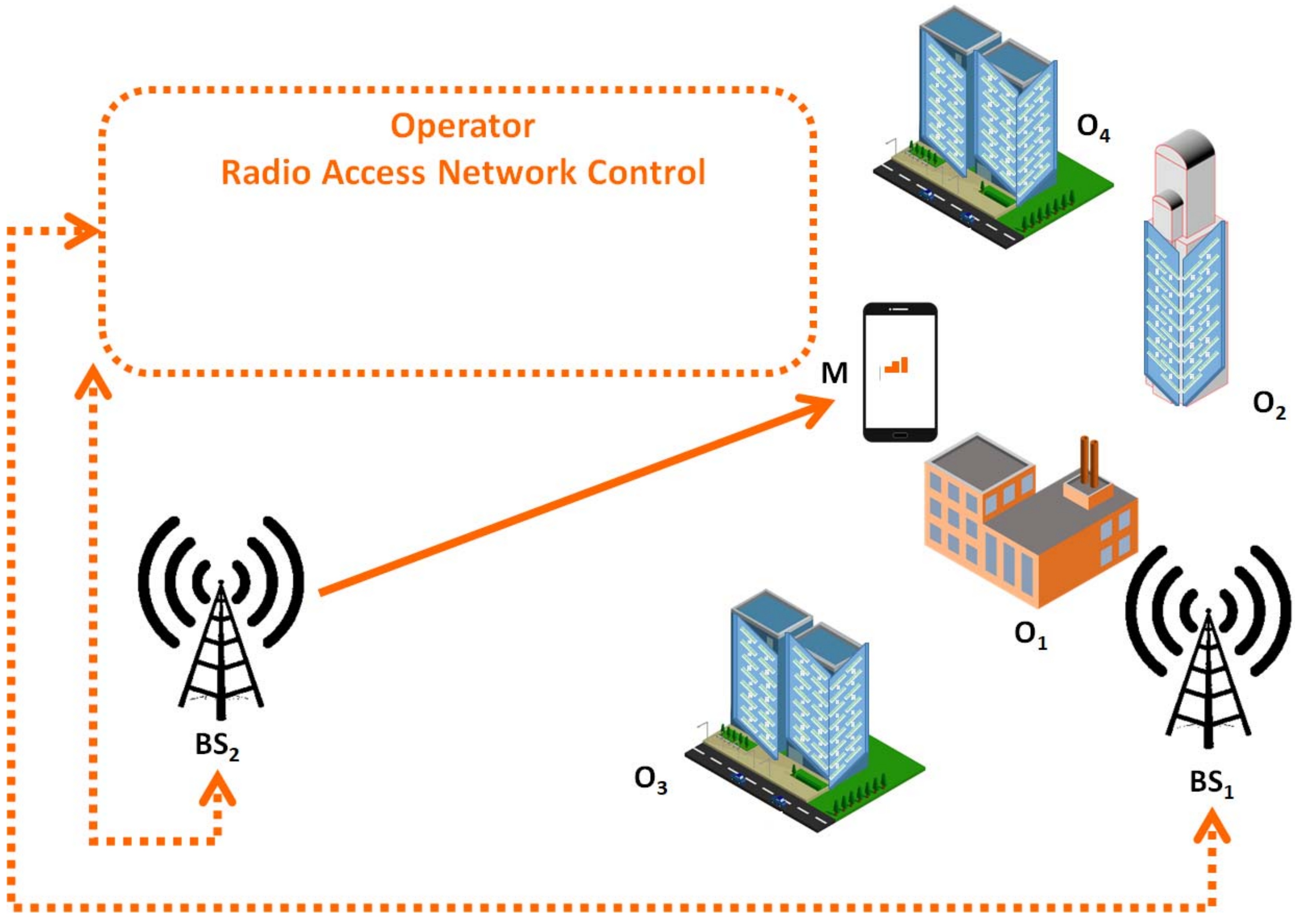
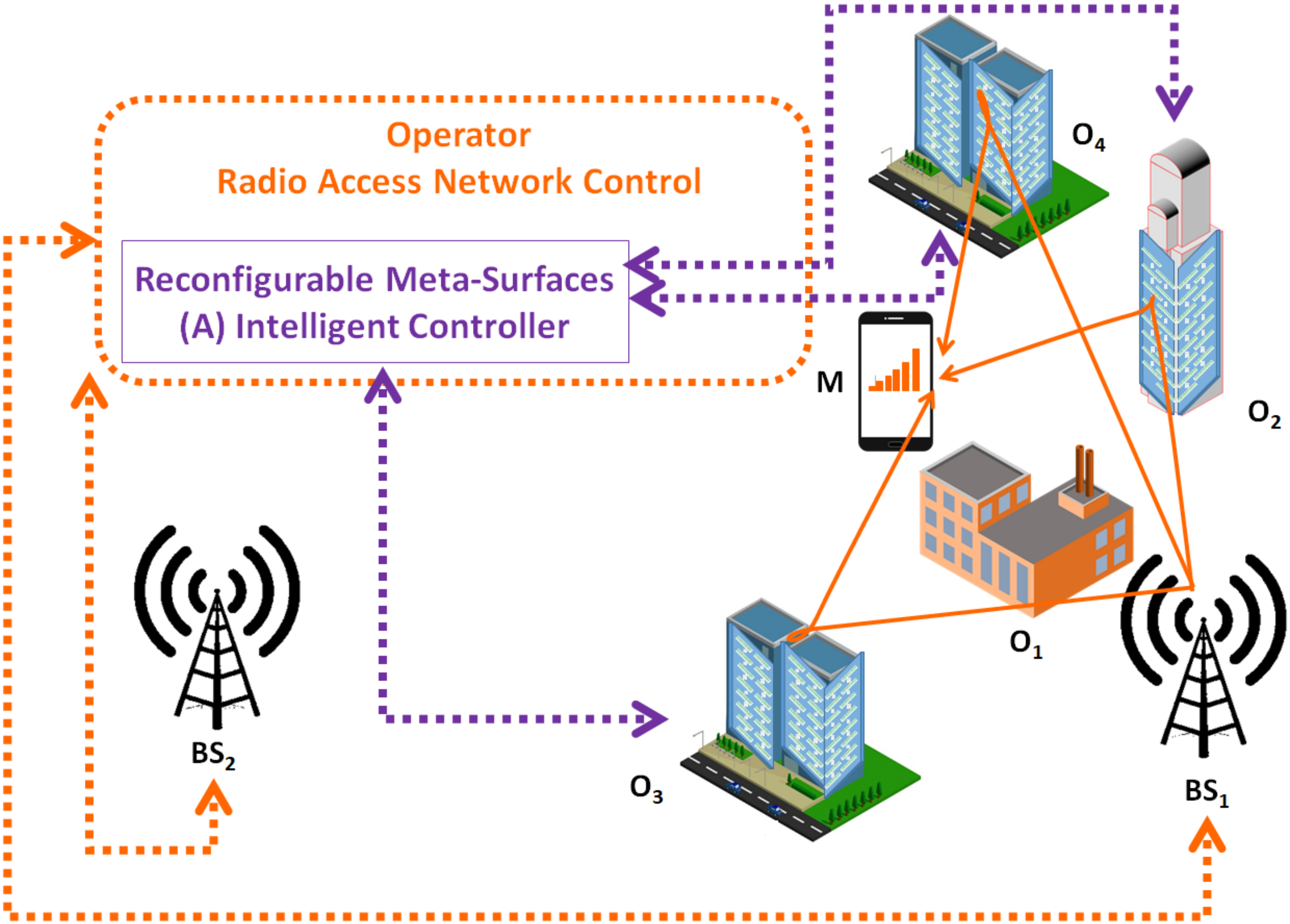


The Brain & Algorithms: Artificial Intelligence



The Brain & Algorithms: Artificial Intelligence



Reconfigurable Intelligent Surfaces (RISs)

What is an RIS ?

What is an RIS ? …A New Antenna Technology for 6G

July 14, 2020

Novel Antenna Technologies

- *Reconfigurable intelligent surface (RIS)* can be used to provide a propagation path where no LoS link exists [25]. An example of signal reflection via RIS is illustrated in Figure 12.

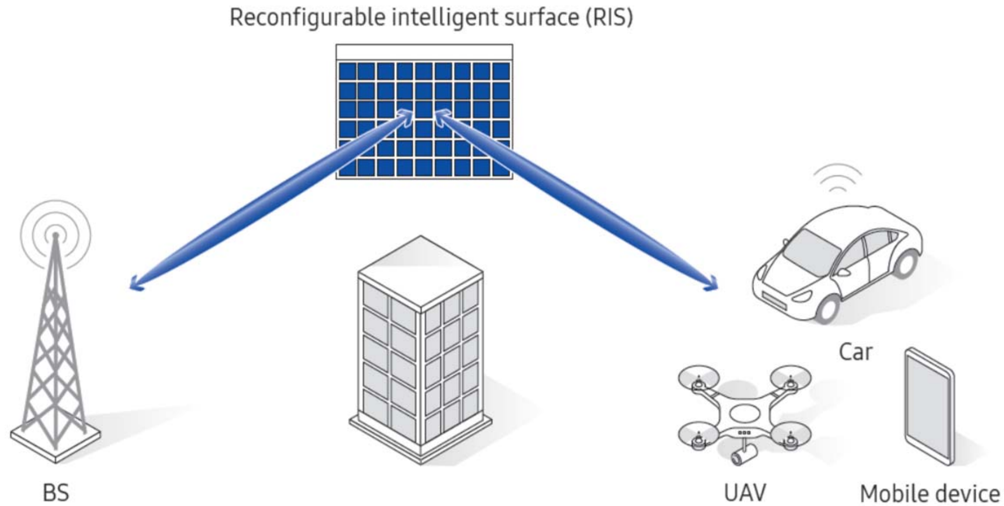


Figure 12

RIS-aided communication between a BS and a mobile user, where the LoS path is blocked.

What Wave Transformations Can an RIS Apply ?

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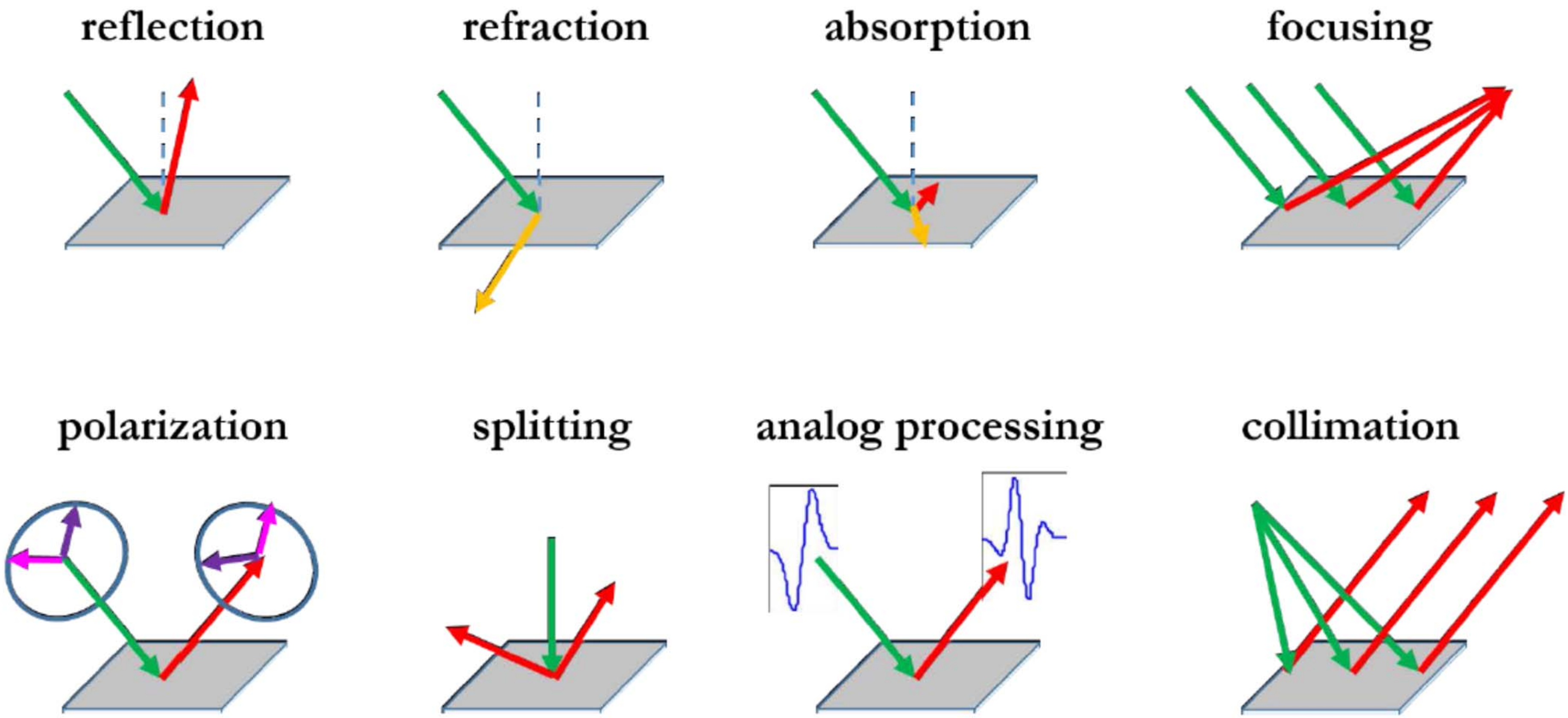

How Does an RIS Look Like ?

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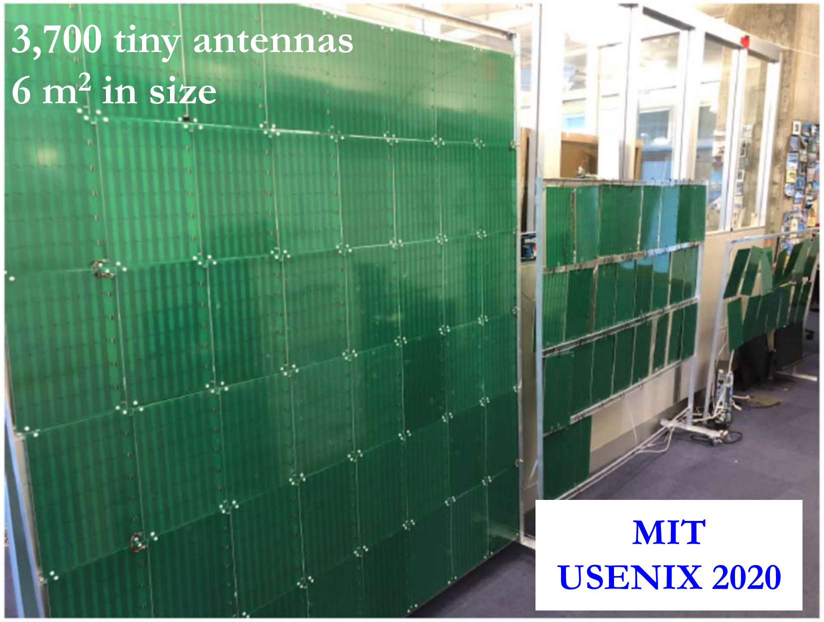
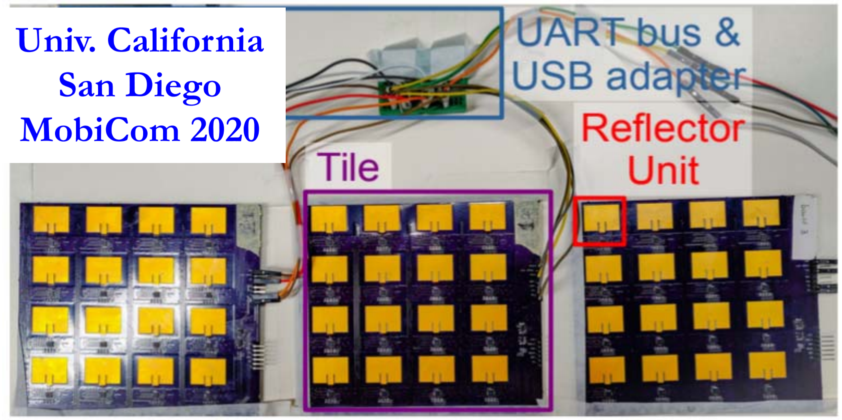
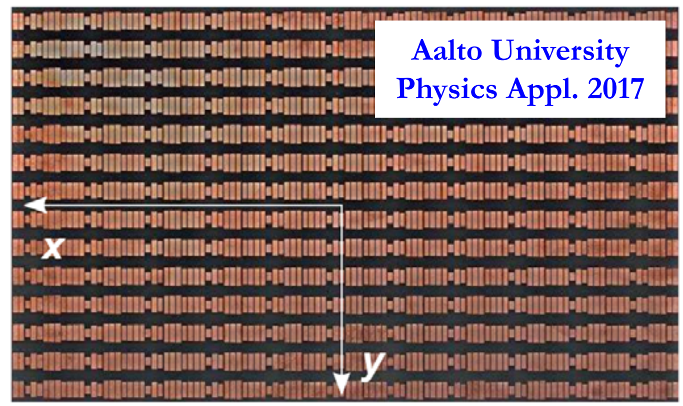
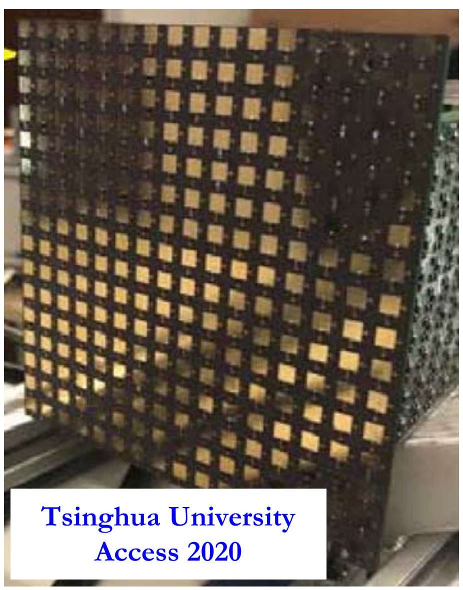
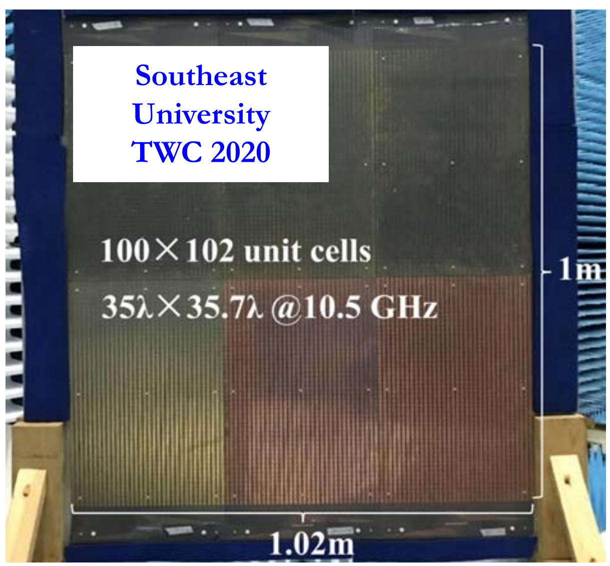
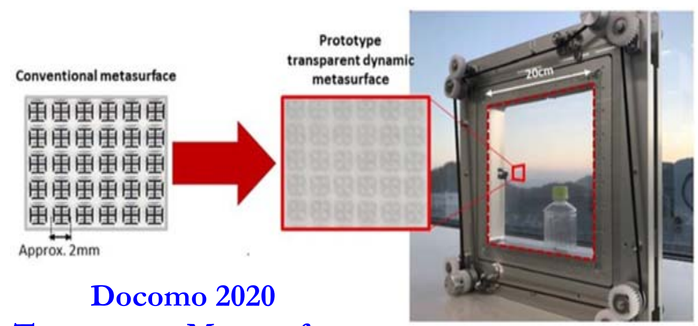










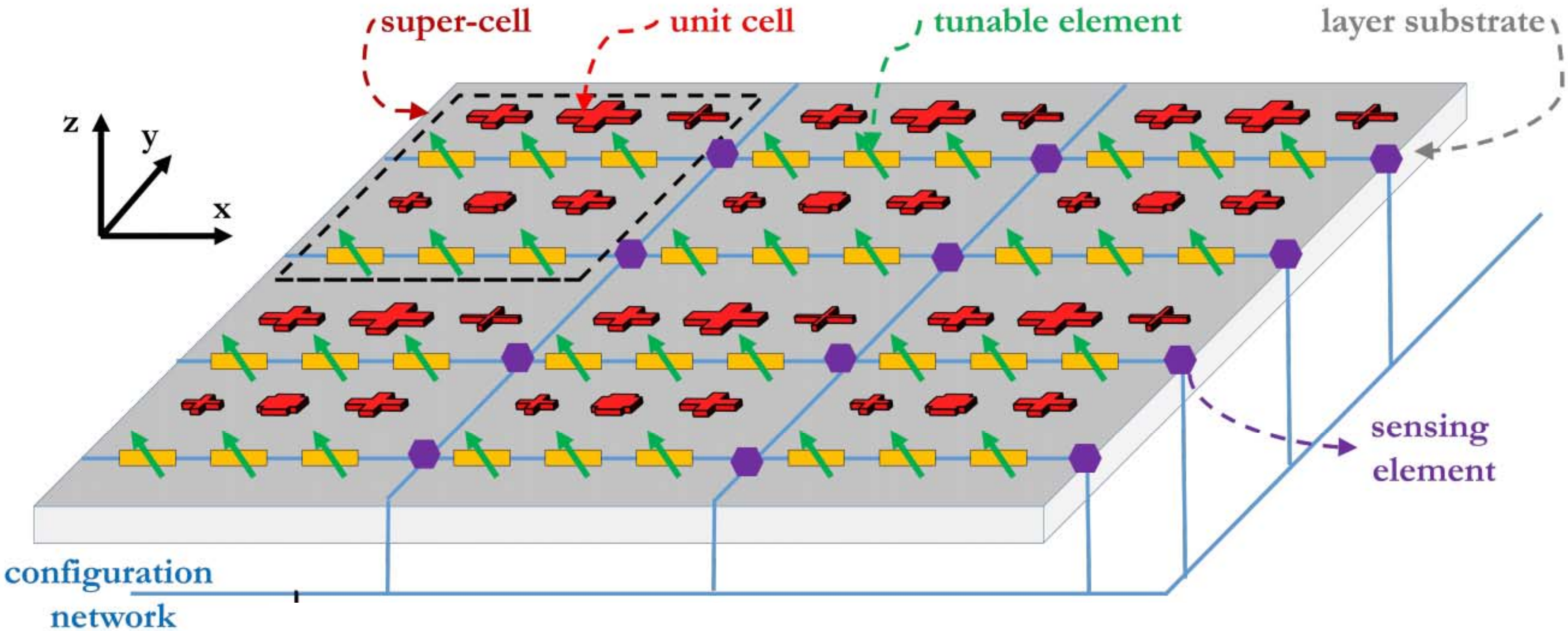


Docomo 2020
Transparent Metasurface

Conceptual Structure

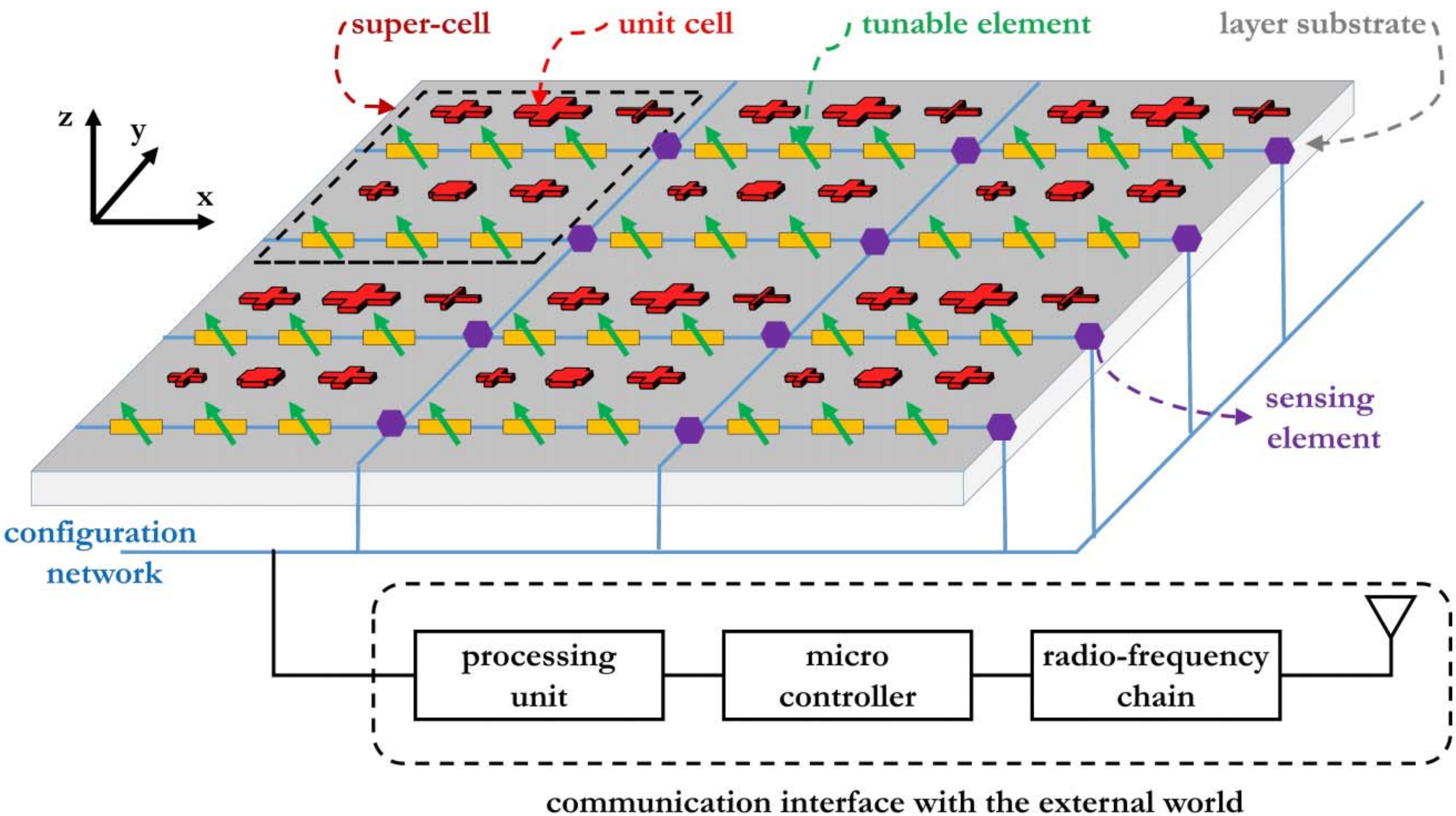
Reconfigurable Intelligent (Meta)Surfaces

Conceptual Structure



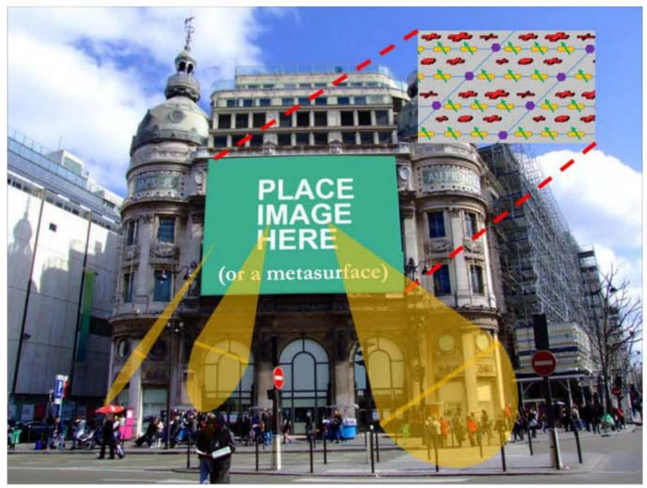
Reconfigurable Intelligent (Meta)Surfaces

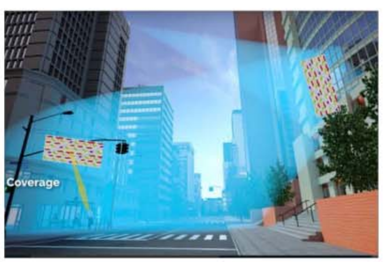
Conceptual Structure and Operation



What is an RIS Useful For ?

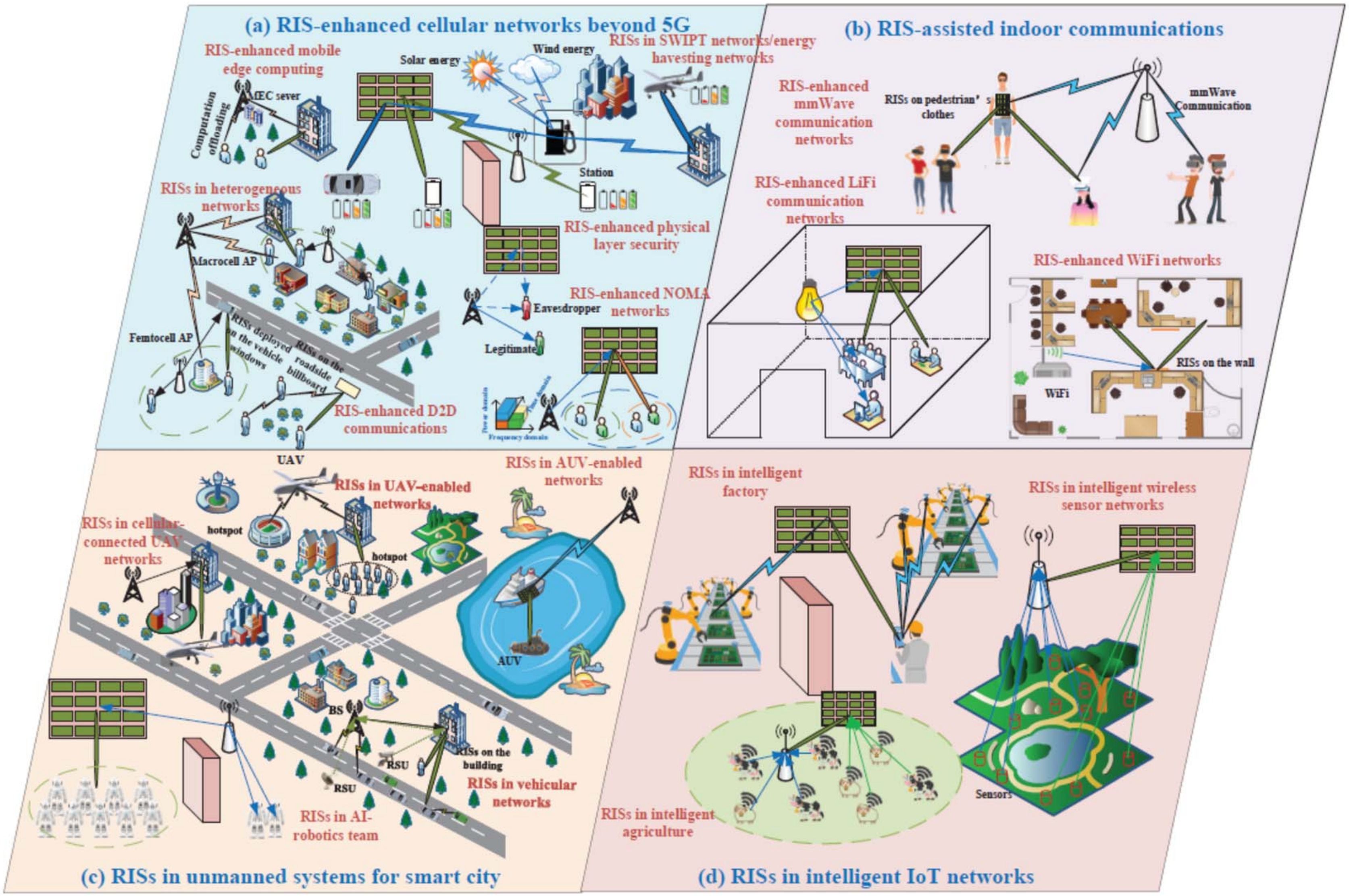
What is an RIS Useful For ? …RIS-Empowered Wireless





M. Di Renzo et al., "Smart Radio Environments Empowered by RISs", arXiv:2007.03435

Enhancing Coverage, Rate, Security Through RISs



Y. Liu, M. Di Renzo et al., "RISs: Principles & Opportunities", arXiv:2007.03435

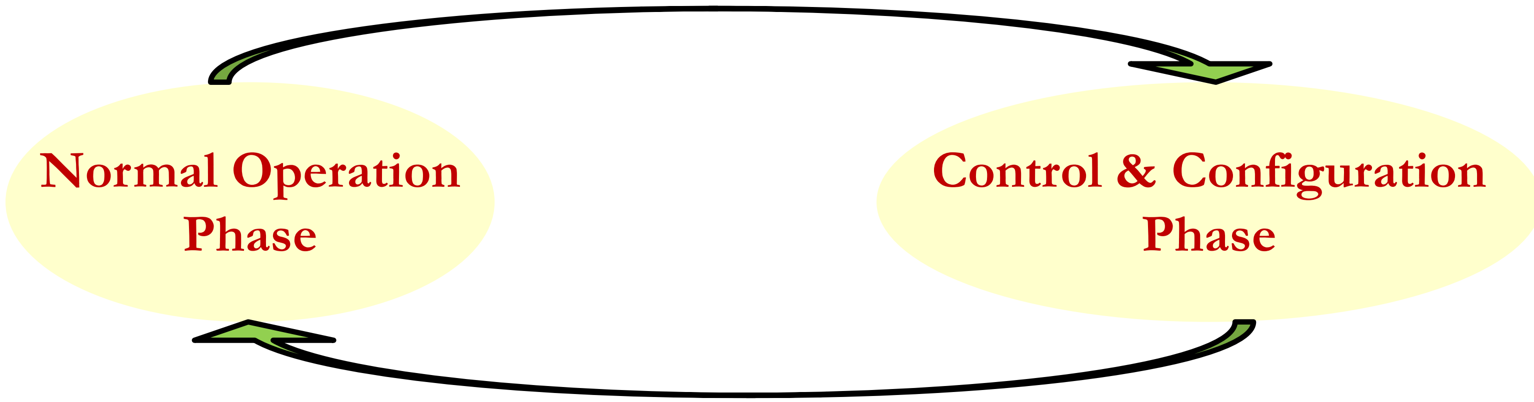
What Does Make an RIS Different ?

What Does Make an RIS Different ?

Nearly-Passive Design / Implementation

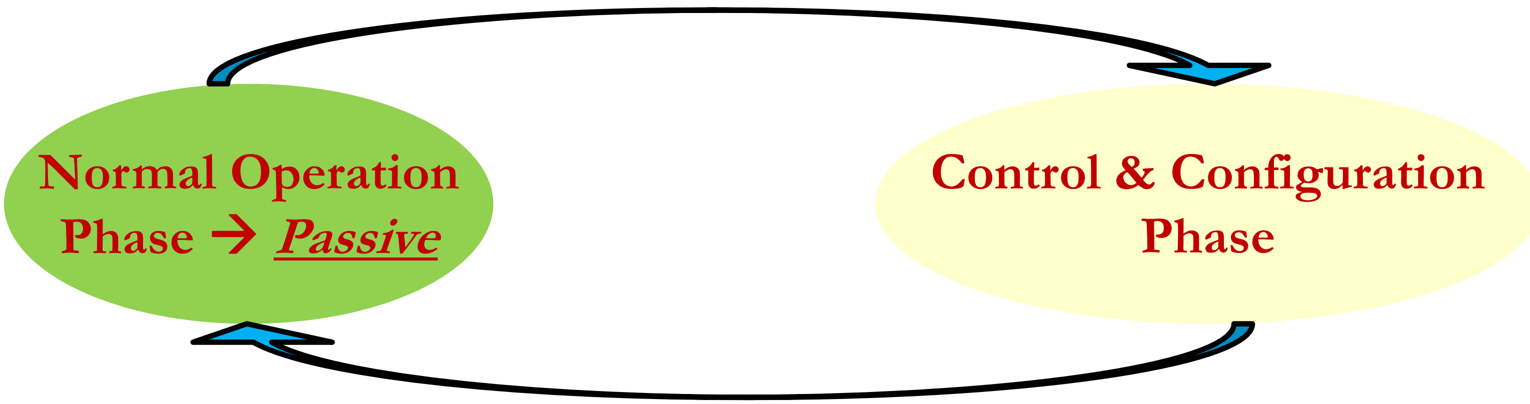
What Does Make an RIS Different ?

Nearly-Passive Design / Implementation



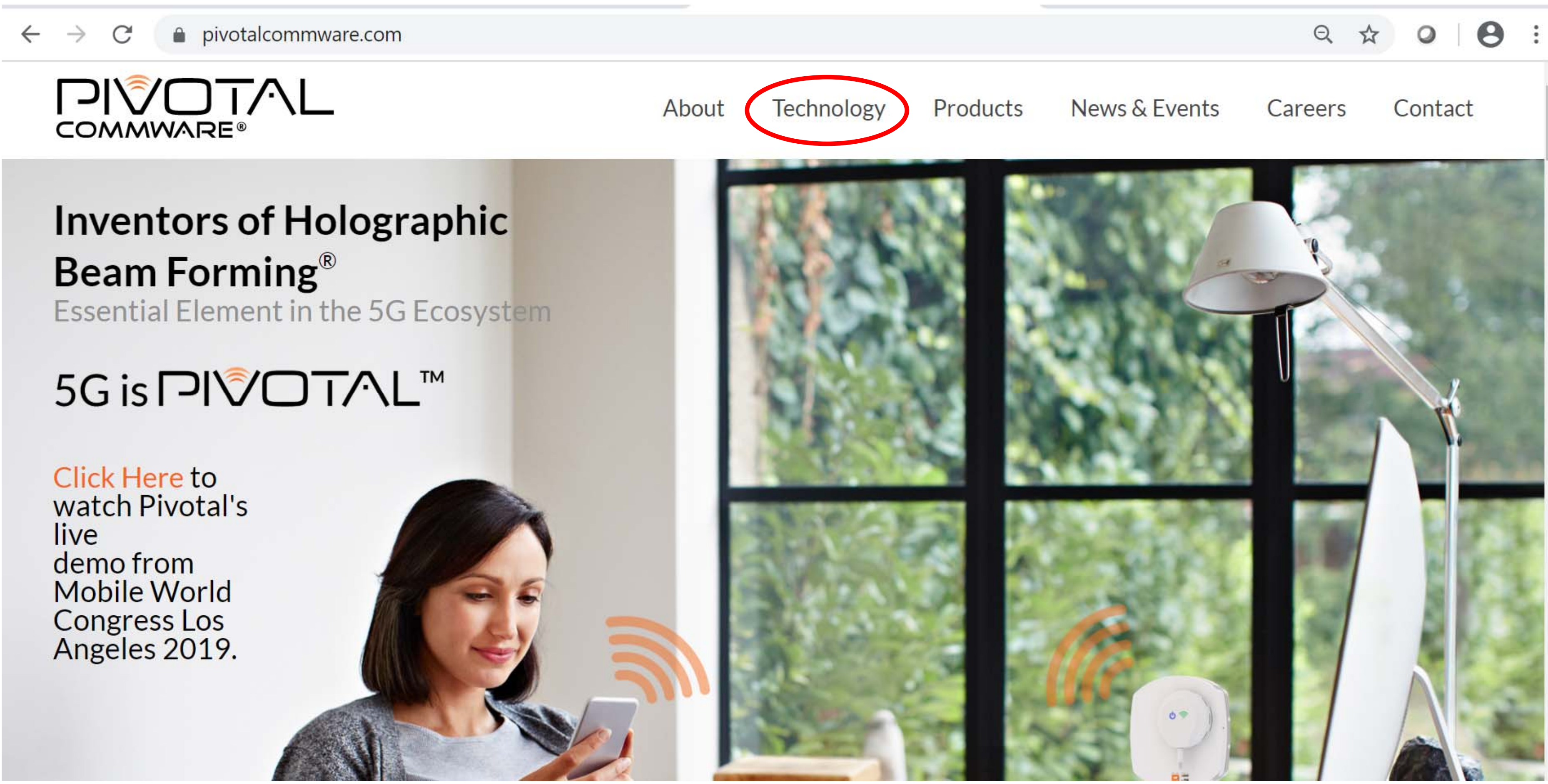
What Does Make an RIS Different ?

Nearly-Passive Design / Implementation



- An RIS is nearly-passive if the following three conditions are fulfilled simultaneously:
  - No power amplification is used after configuration (during the normal operation phase)
  - Minimal digital signal processing capabilities are needed only to configure the surface (during the control and programming phase)
  - Minimal power is used only to configure the surface (during the control and programming phase)

What Does Make an RIS Different ?



Example of Power Consumption

What Does Make an RIS Different ?

Example of Power Consumption

	Phased Array	RIS HBF	Unit
Number of Unit Cells	256	640	#
Antenna Gain	28	26	dB
Number of RF chains	256	1	#
Transmit Power per chain	6.2	2512	mW
Total RF Transmit Power	1.58	2.51	W
Power Added Efficiency	4.0%	25.0%	%
DC Draw for RF	39.6	10.0	W
HBF Controller	0	2.9	W
Total DC Power	**39.6**	**12.9**	**W**

What Does Make an RIS Different ?

Example of Power Consumption

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Compared with other transmission technologies, e.g., phased arrays, multi-antenna transmitters, and relays, RISs require the largest number of scattering elements, but each of them needs to be backed by the fewest and least costly components. Also, no power amplifiers are usually needed.

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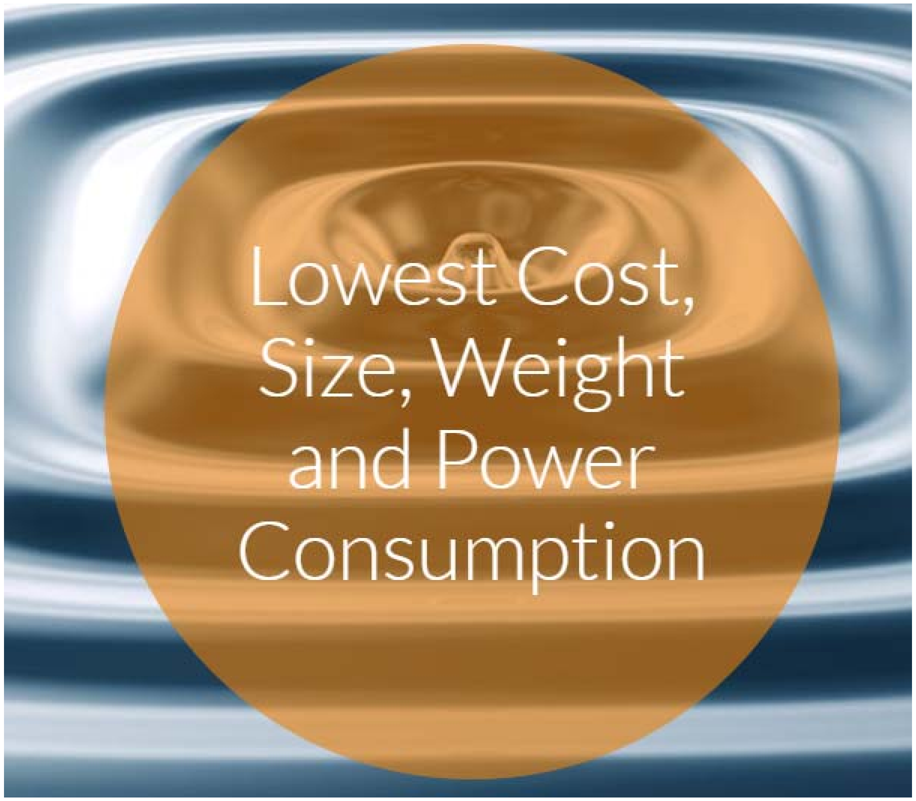
… no free lunch rule …

What Does Make an RIS Different ?

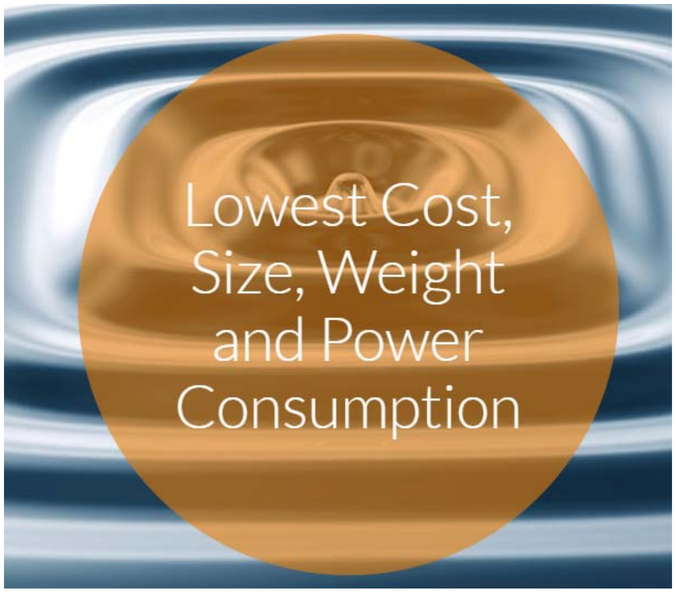
C-SWaP



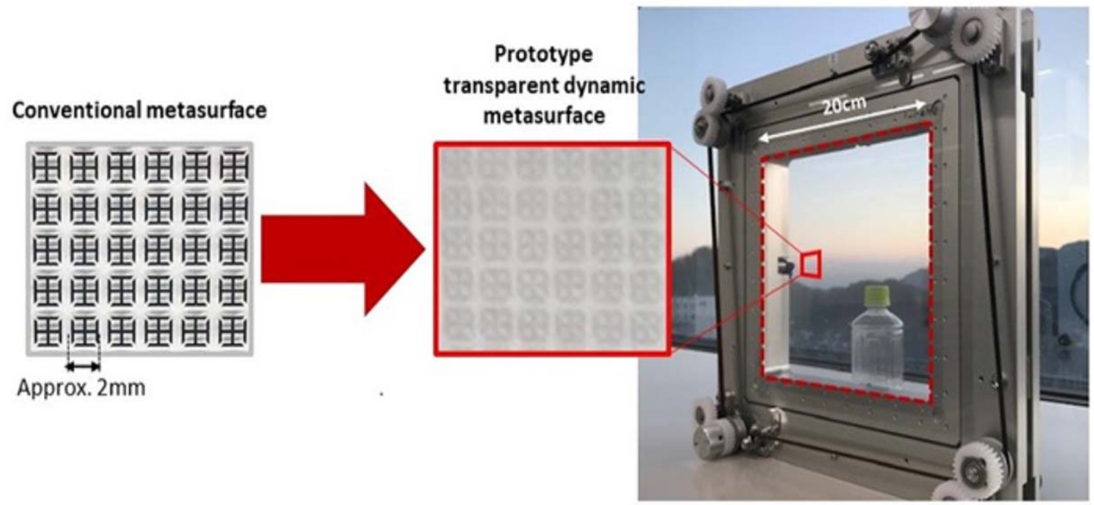
For these reasons, RISs may constitute an emerging and promising software-defined architecture that can be realized at reduced cost, size, weight, and power (C-SWaP design)

What Does Make an RIS Different ?

C-SWaP

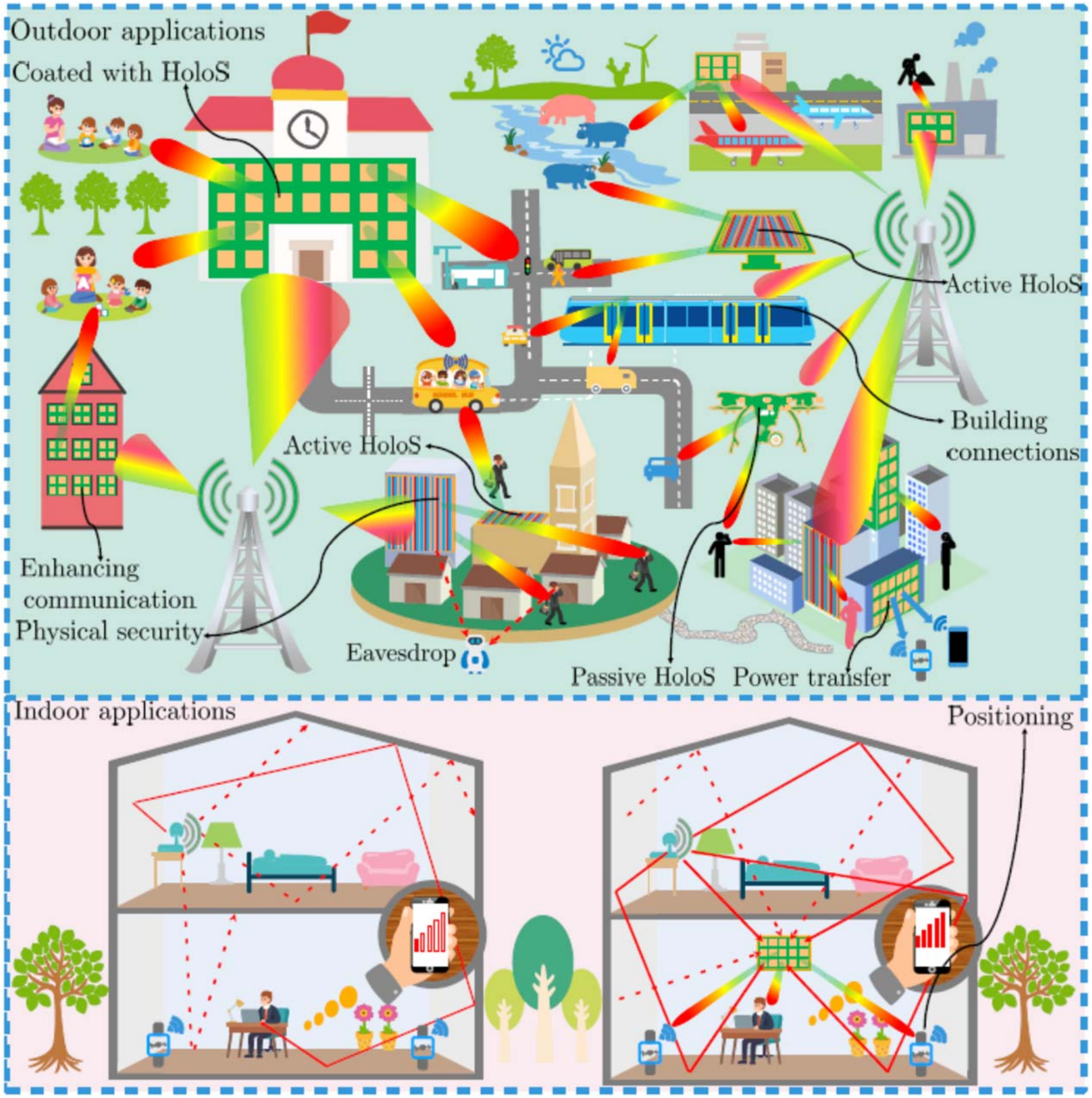


Docomo 2020
Transparent Metasurface



Sustainable wireless design (e.g., low EMF exposure) without generating new waves and possibly made of physically & aesthetically unobtrusive and recyclable material

Joint Active & Passive Wireless Networks Design



"RISs can fundamentally transform today's wireless networks with active nodes solely to a new hybrid network comprising active and passive components co-working in an intelligent way, in order to achieve a sustainable capacity growth with low and affordable cost and power consumption"

C. Yuen, M. Di Renzo et al., "Holographic MIMO Surfaces for 6G", arXiv:1911.12296

Expert Knowledge Aided Machine Learning

Wireless Networks Design in the Era of ML

MODEL-AIDED WIRELESS ARTIFICIAL INTELLIGENCE

Embedding Expert Knowledge in Deep Neural Networks for Wireless System Optimization

M. Di Renzo et al., Special Issue on 6G, Veh. Technol. Mag. 2020 (arXiv:1808.01672)

The Question

The Question (…from a wireless perspective…)

What can machine learning do for communication theory ?

The Question (…from an ML perspective…)

What can communication theory do for machine learning ?

The Question

Can we merge theoretical models with data-driven methods taking the best of both worlds ?

Optimization in Wireless Networks

- **Given some input**

Optimization in Wireless Networks

- Given some input
- We wish to compute the optimal output

Optimization in Wireless Networks

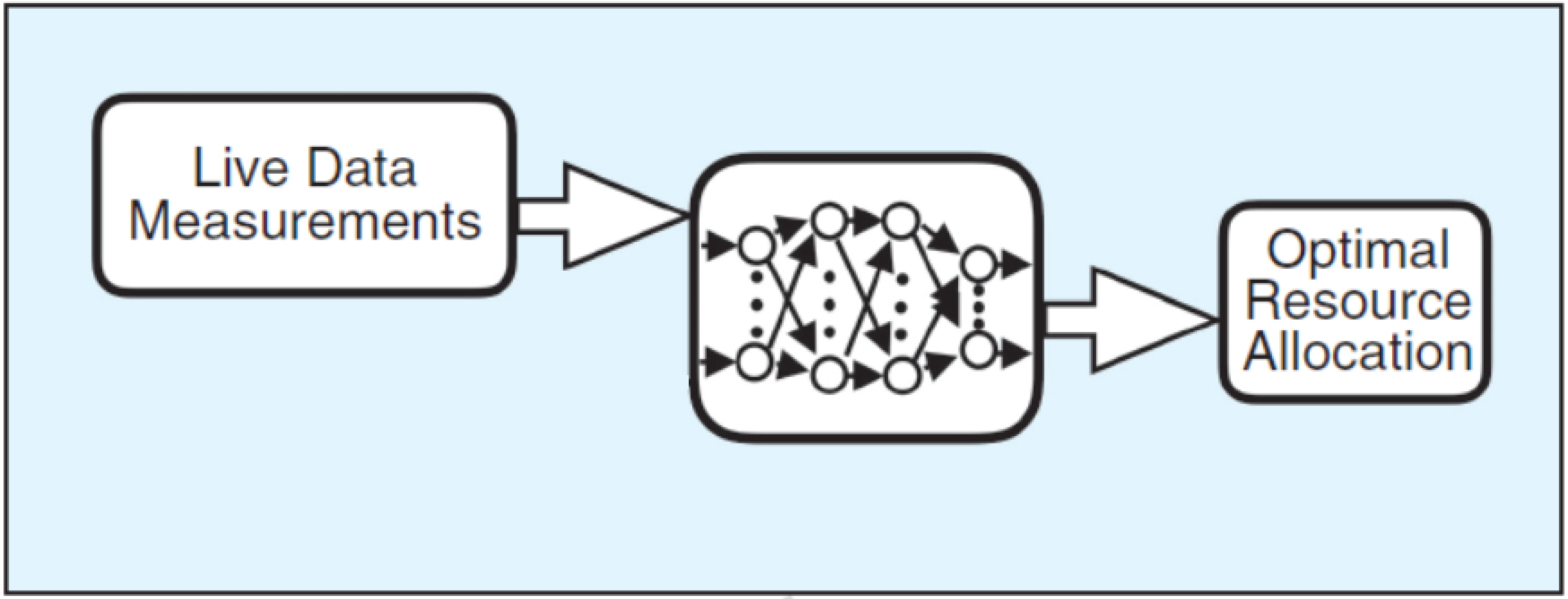
- Given some input
- We wish to compute the optimal output
- That optimize the network performance

$$y_1 = F(x_1)$$
$$y_2 = F(x_2) \Rightarrow$$
$$\vdots$$

Computing the optimal mapping F

"Learning to Optimize" Wireless Networks

… the "conventional" data-driven approach …



"Learning to Optimize" Wireless Networks

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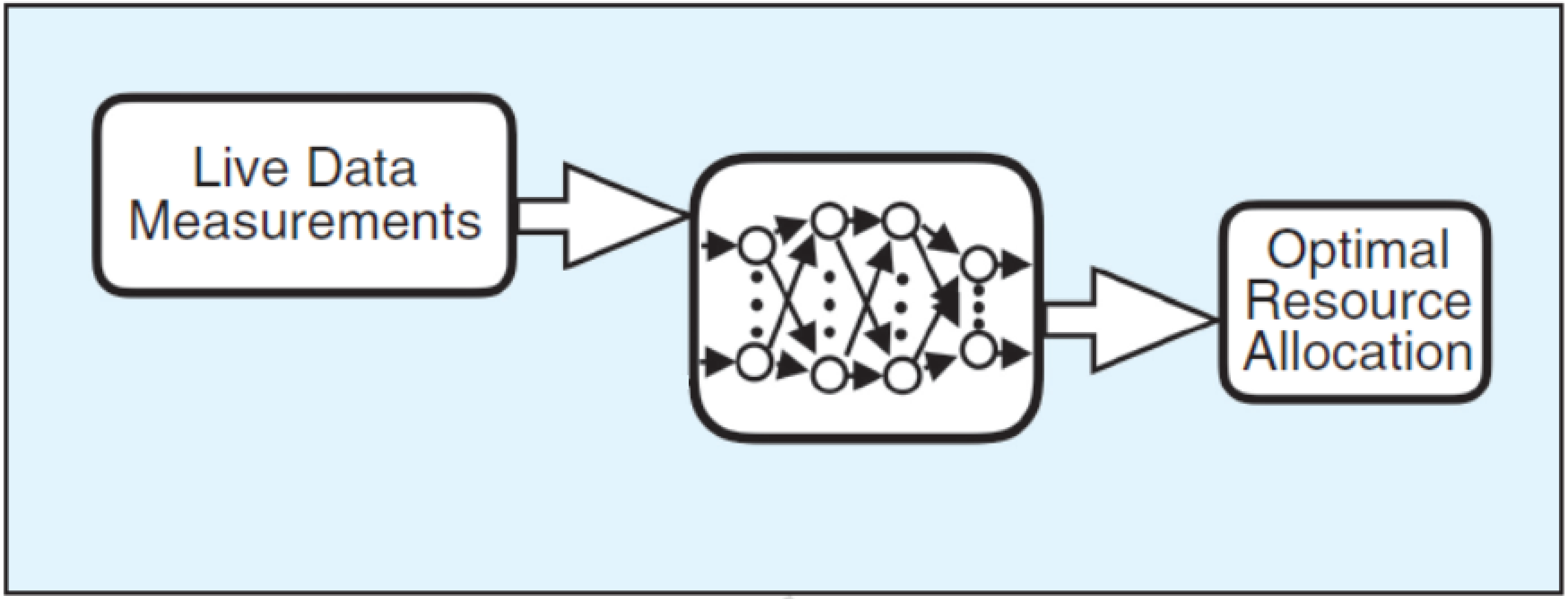


- **Lots of data & interpretation of data**
- **Brute-force optimization**

How About the Quality of Data and Bias ?

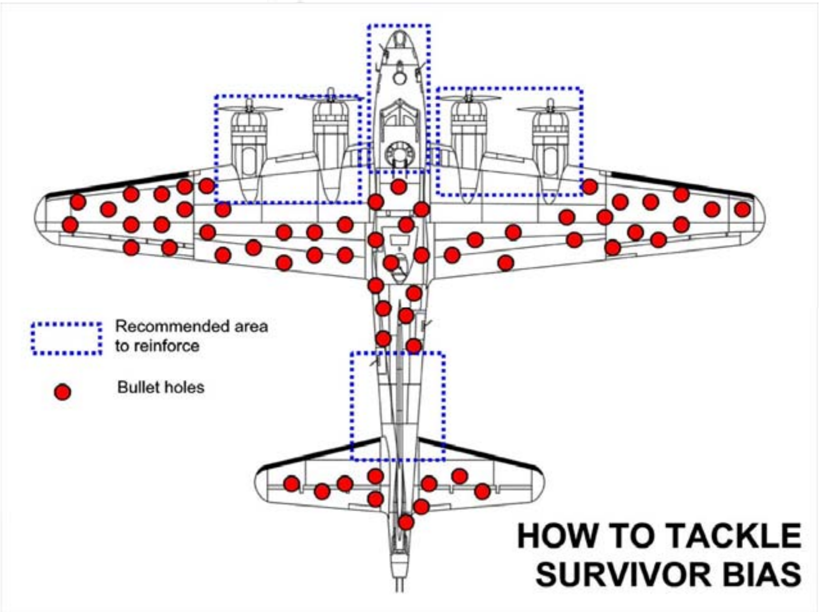
More on Bias: Survivorship Bias in Subsurface Modeling?

Michael Pyrcz, University of Texas at Austin (@GeostatsGuy)

Example shared in my Introduction to Geostatistics class by @uddhav_marwaha (Twitter).

Survivorship Bias: a form of selection bias resulting from selecting samples that "survived" some previous selection process. This often leads to false conclusions. For example, in WWII the Center for Naval Analyses (@CNA_org Twitter) compiled a dataset of bomber damage to assess where reinforcement was needed. Statistician Abraham Wald recognized this was a case of survivorship bias. The plans shot in critical locations did not return to base. Wald suggested reinforcement of locations that were not damaged in planes that safely returned to base! (https://en.wikipedia.org/wiki/Survivorship_bias#In_the_military)

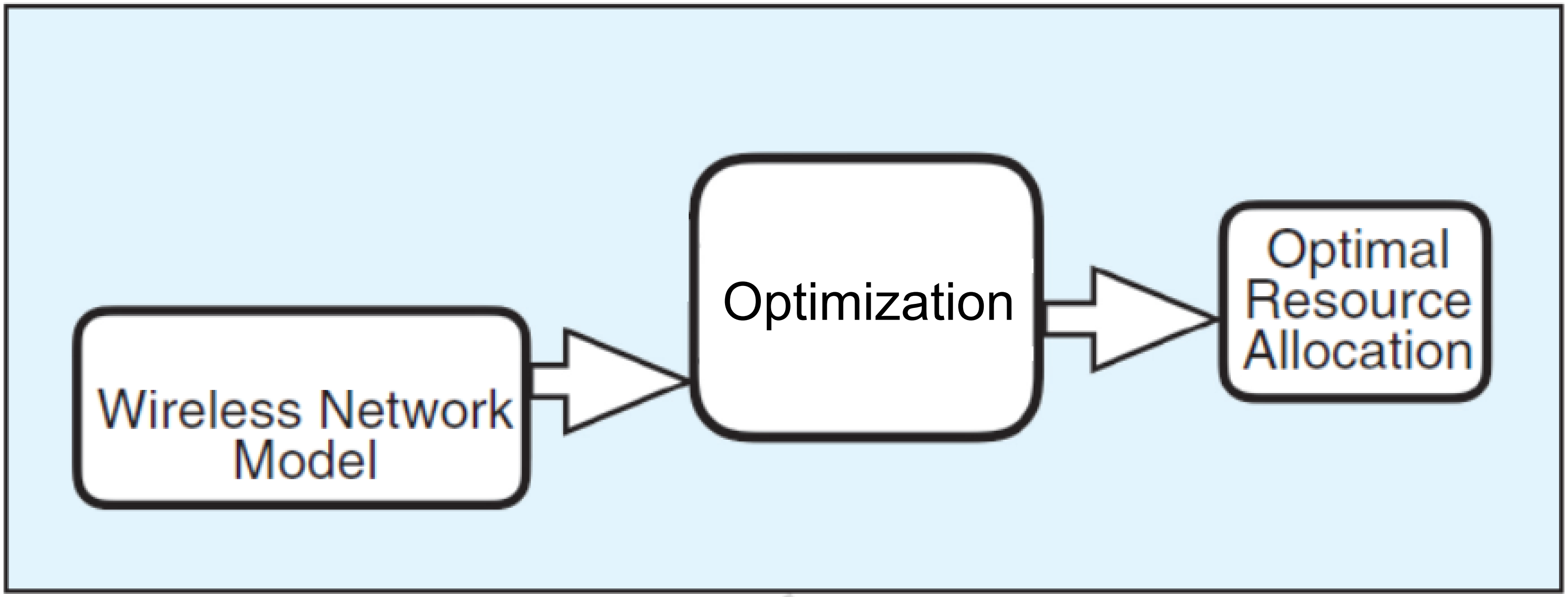
Is there preselection in our subsurface datasets? For our subsurface projects do we only sample: success cases, producing wells, drill holes with economic ore grades, large fields, clastic depositional settings, marine seismic surveys, high resolution 3D seismic surveys, shallow reservoirs etc. When we pool samples, check for preselection and ensure this is considered in the resulting inferences and decision to export these results. The samples must be representative of the population to which we will apply our model. Of course, this applies to any datasets.



Hypothetical dataset of aircraft damage for planes that returned to based. Source https://en.wikipedia.org/wiki/Survivorship_bias#/media/File:Survivorship-bias.png

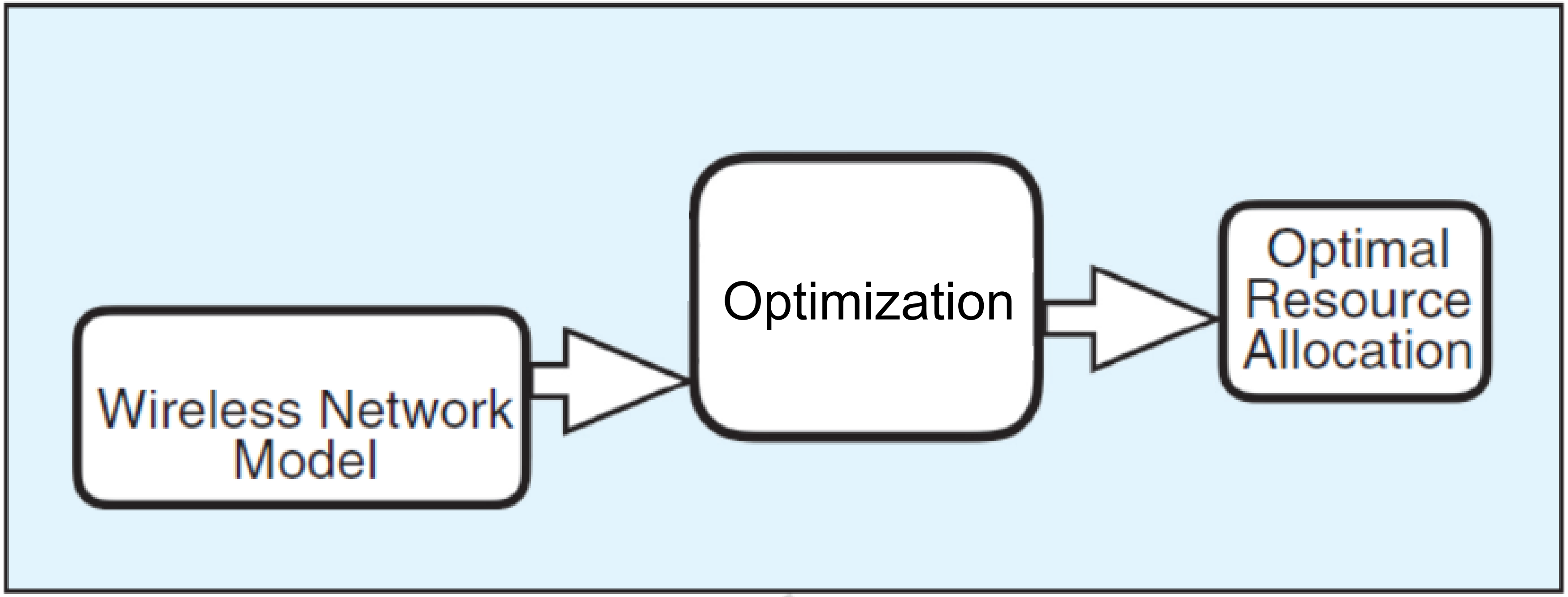
“Modeling to Optimize” Wireless Networks

… the “conventional” comm-theoretic approach …



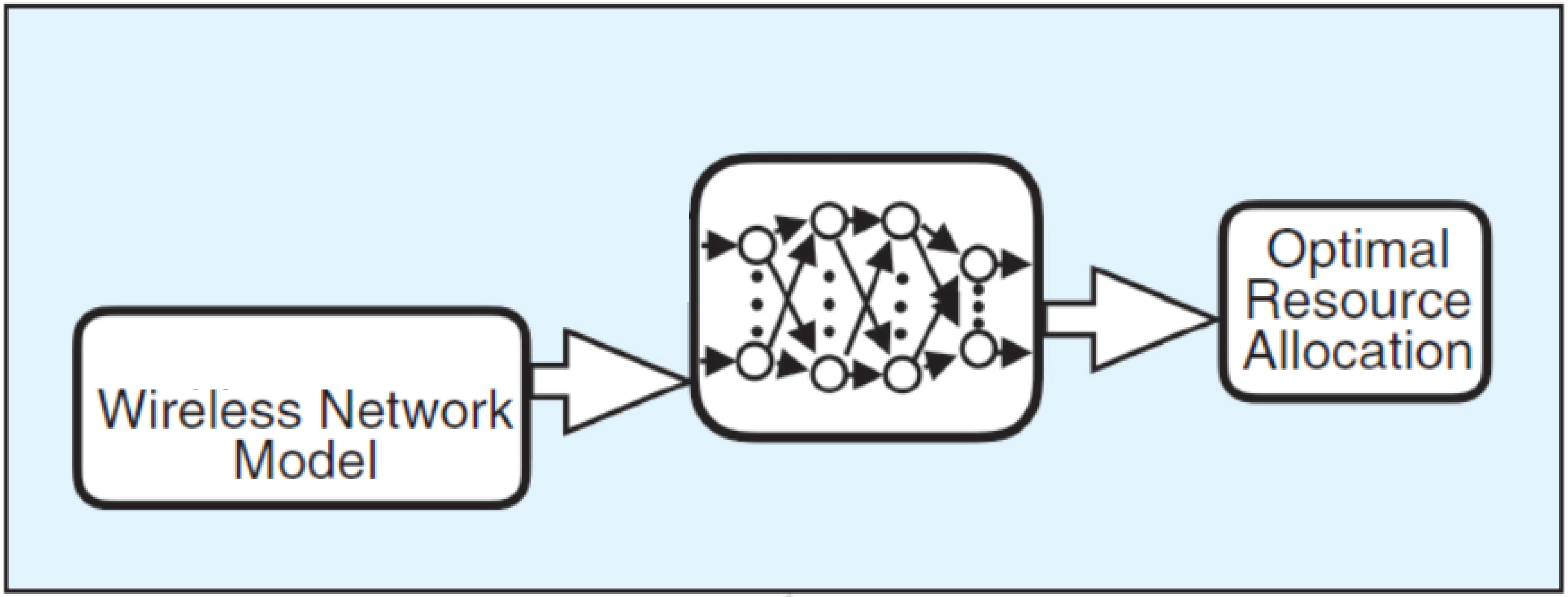
“Modeling to Optimize” Wireless Networks

… the “conventional” comm-theoretic approach …



- ❑ **Non-convex mixed-integer optimization**
- ❑ **Real-time implementation is “challenging”**

"Modeling to Optimize" Wireless Networks by ANNs



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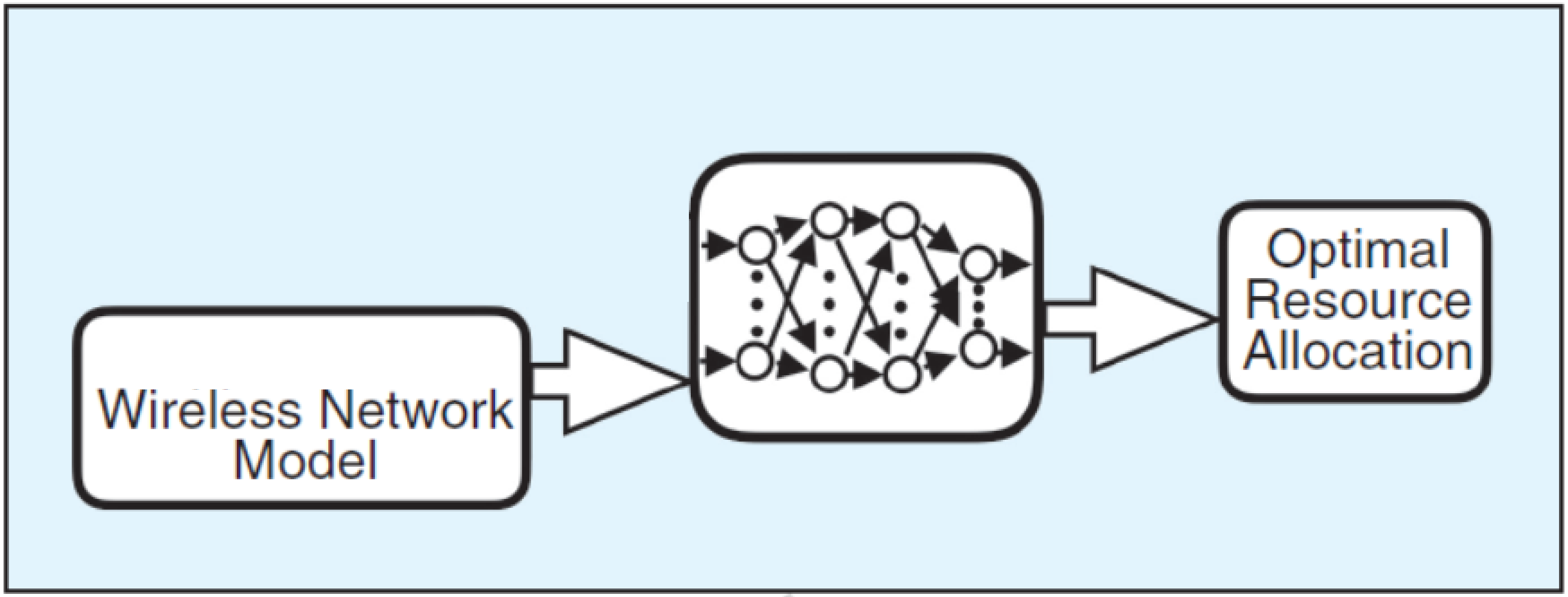

- After training, computationally simple
- But, modeling mismatch is an issue

Modeling Assumption A, … Modeling Assumption Z

… excerpts from a paper of mine …

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Under the assumption that the BSs are modeled as points of a homogeneous PPP and that the events that the BS-to-MT links are in LOS, NLOS or outage state are independent, Ψ can be partitioned into three (one for each link state) independent and non-homogeneous PPPs, *i.e.*, Ψ_{LOS}, Ψ_{NLOS} and Ψ_{OUT}, such that $\Psi = \Psi_{\mathrm{LOS}} \cup \Psi_{\mathrm{NLOS}} \cup \Psi_{\mathrm{OUT}}$. This originates from the thinning property of the PPPs [17]. From (4), the densities of the PPPs Ψ_{LOS}, Ψ_{NLOS} and Ψ_{OUT} are equal to $\lambda_{\mathrm{LOS}}(r) = \lambda p_{\mathrm{LOS}}(r)$, $\lambda_{\mathrm{NLOS}}(r) = \lambda p_{\mathrm{NLOS}}(r)$ and $\lambda_{\mathrm{OUT}}(r) = \lambda p_{\mathrm{OUT}}(r)$, respectively.

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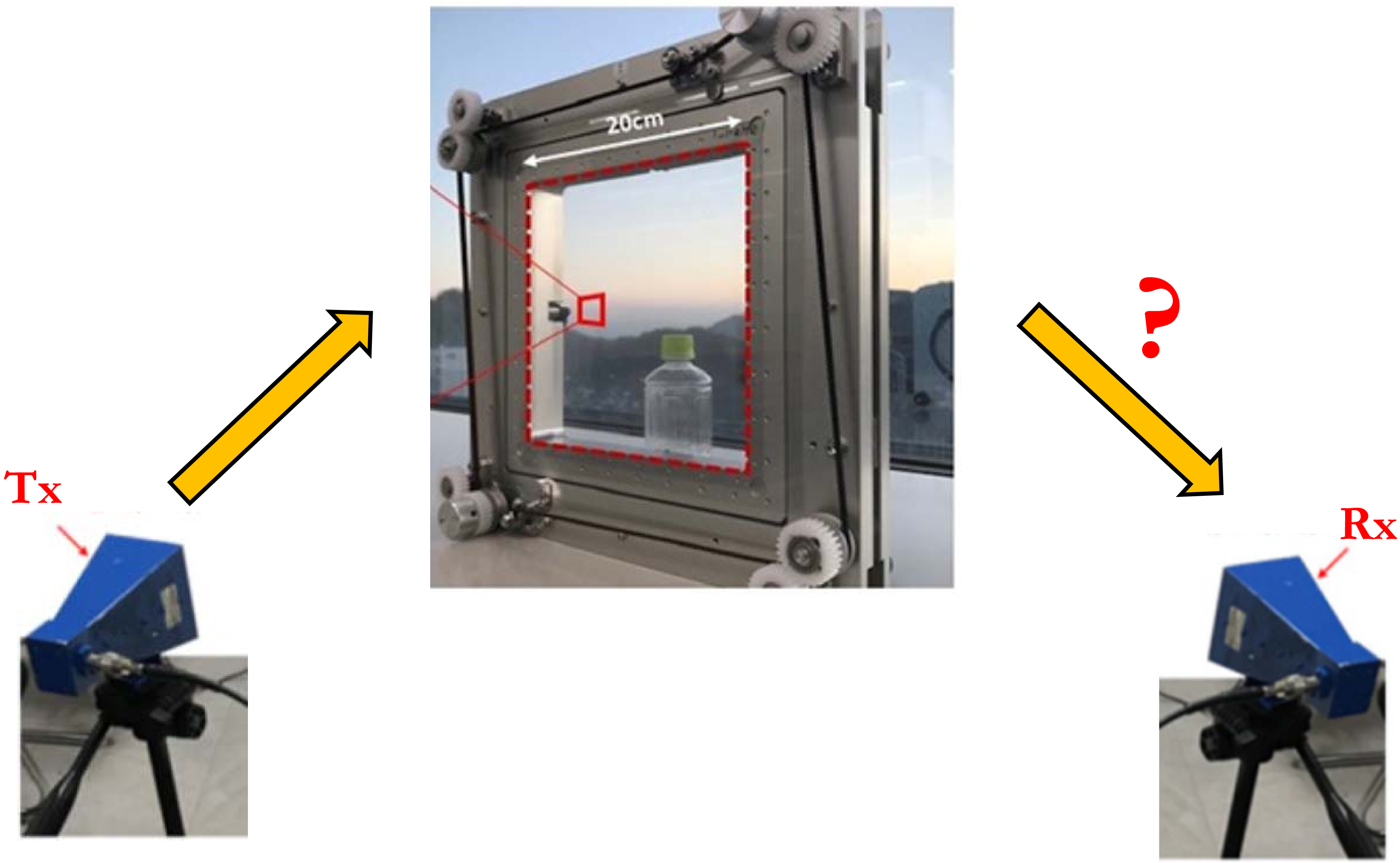
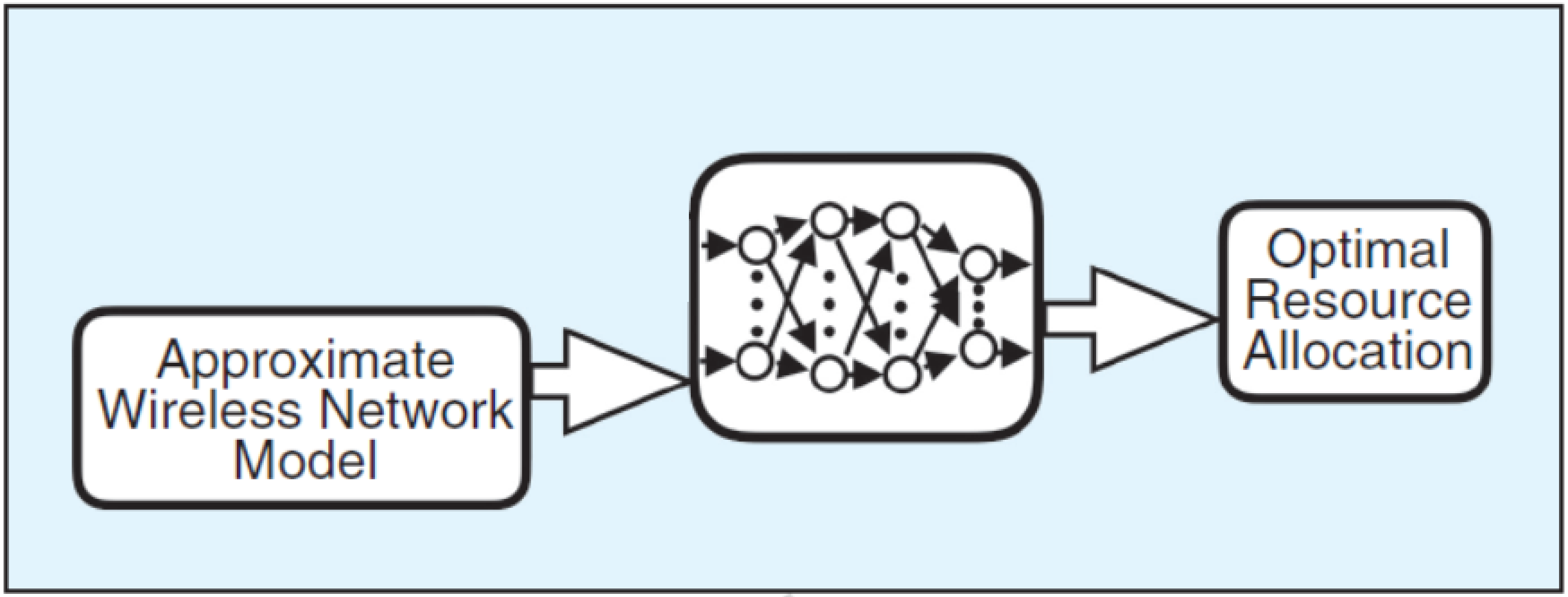
How Many "Comfortable" Assumptions Do We Need ?

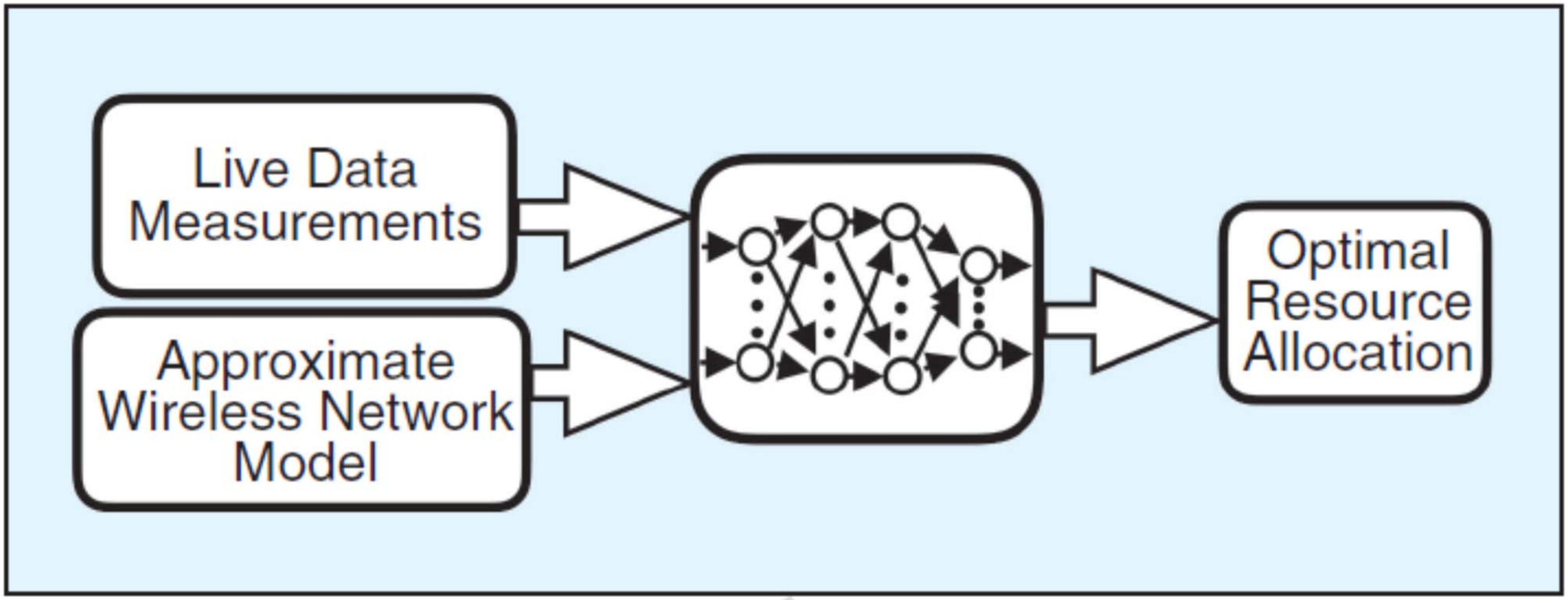


“Modeling to Optimize” Wireless Networks by ANNs



Wireless Networks Design by "Transfer Learning"

… combining live data and models …



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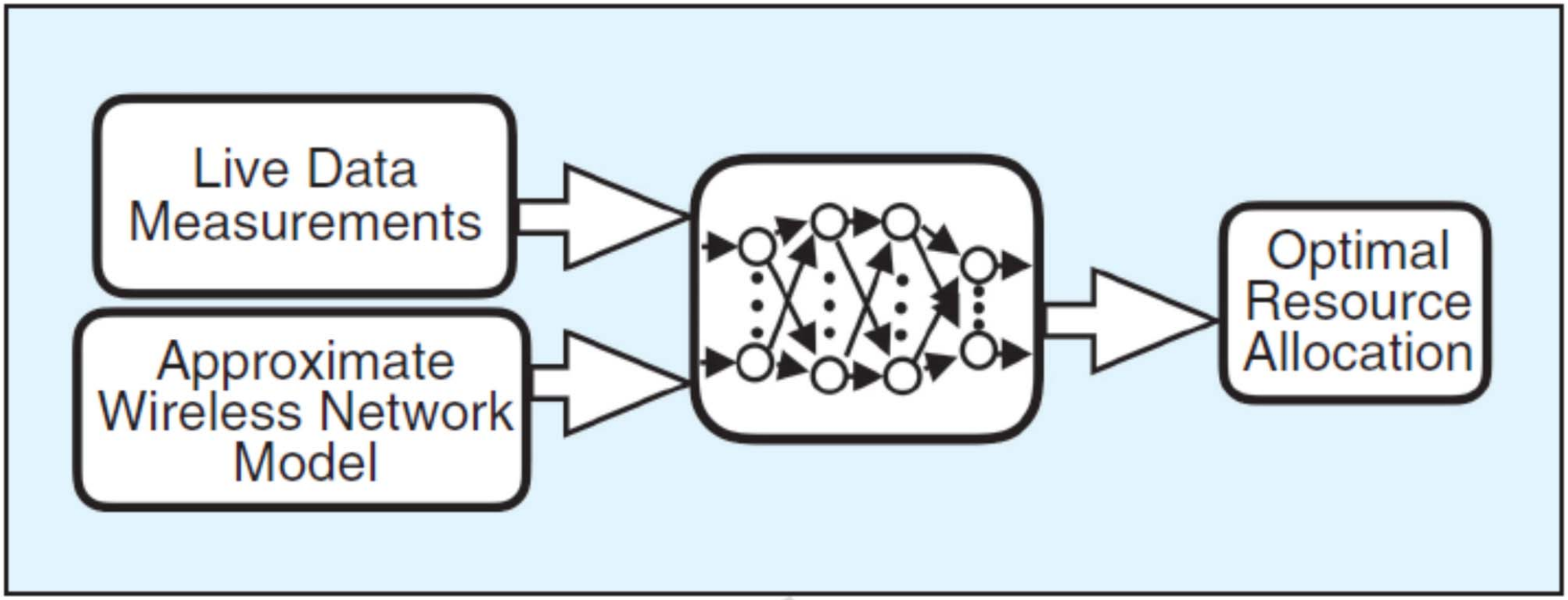

- ❑ Correcting the model mismatch → Less live data ?
- ❑ Reduced complexity at "run time" (after training)

Deep Learning for Wireless

C.1: An accurate and tractable theoretical model is available (e.g., point-to-point channel capacity, point-to-point bit error probability).

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Model-Aided AI – Learning & Refining a Model

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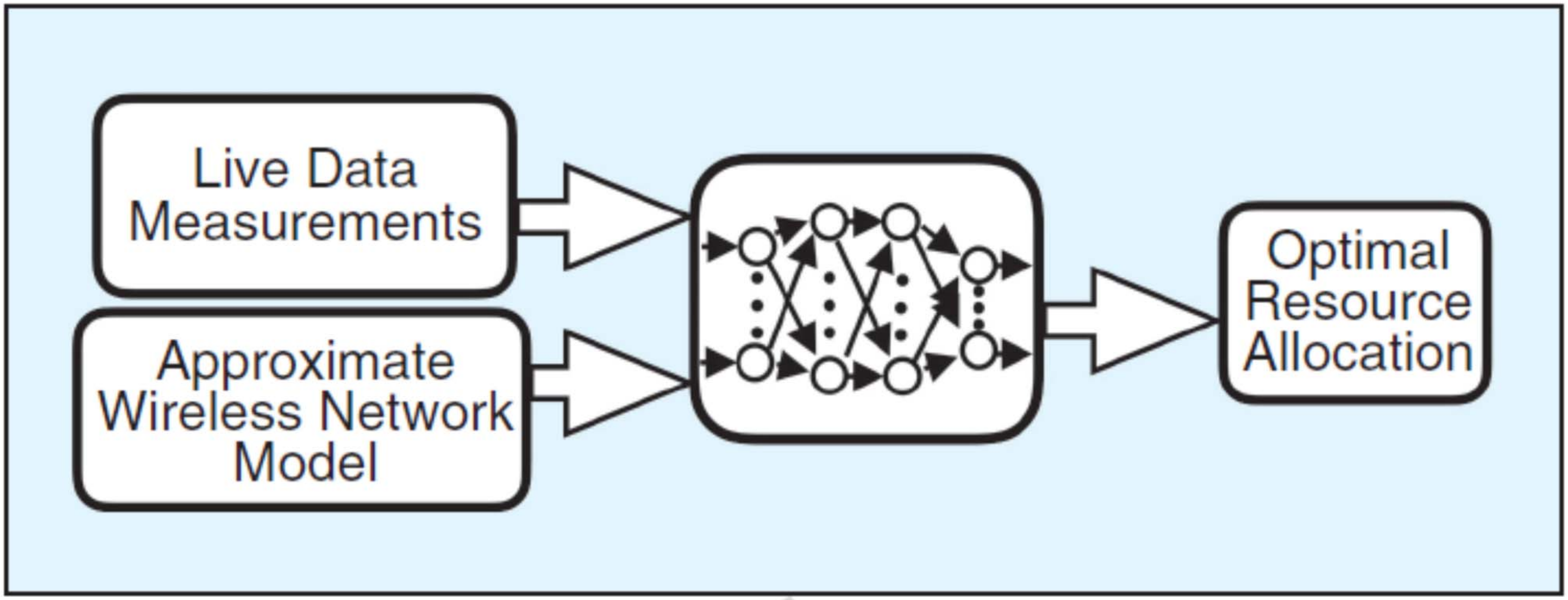
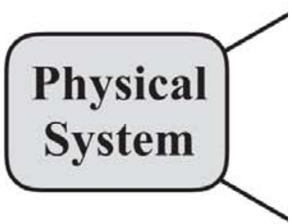
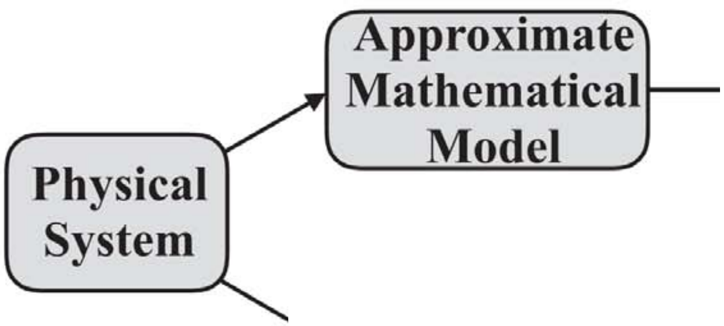
On "Transfer Learning" to Design Wireless Networks



Joint Model-Aided and Data-Driven Optimization



Joint Model-Aided and Data-Driven Optimization



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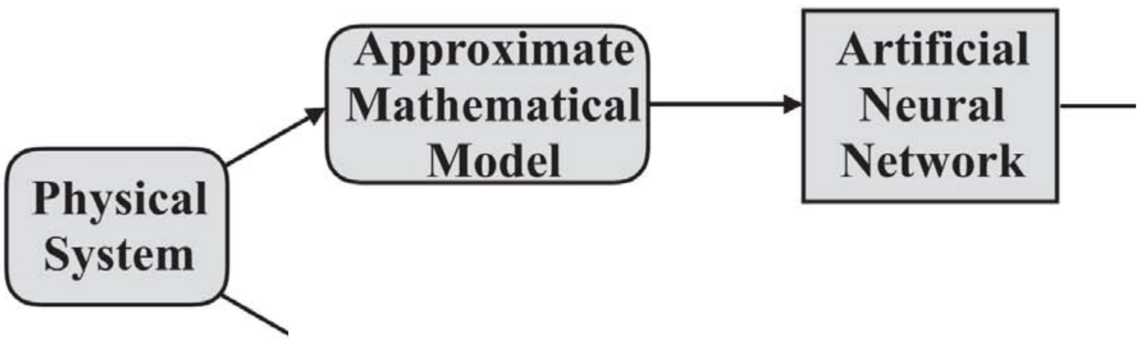

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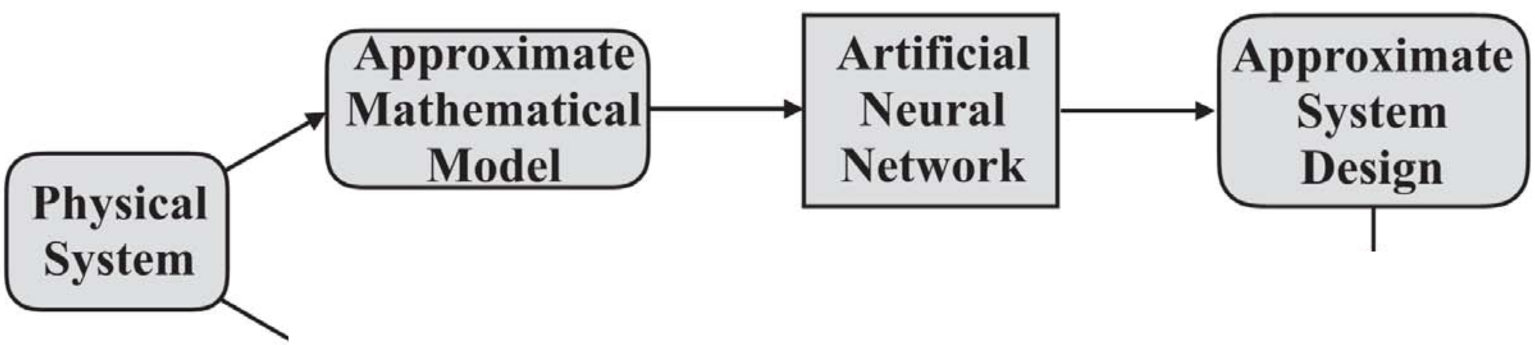

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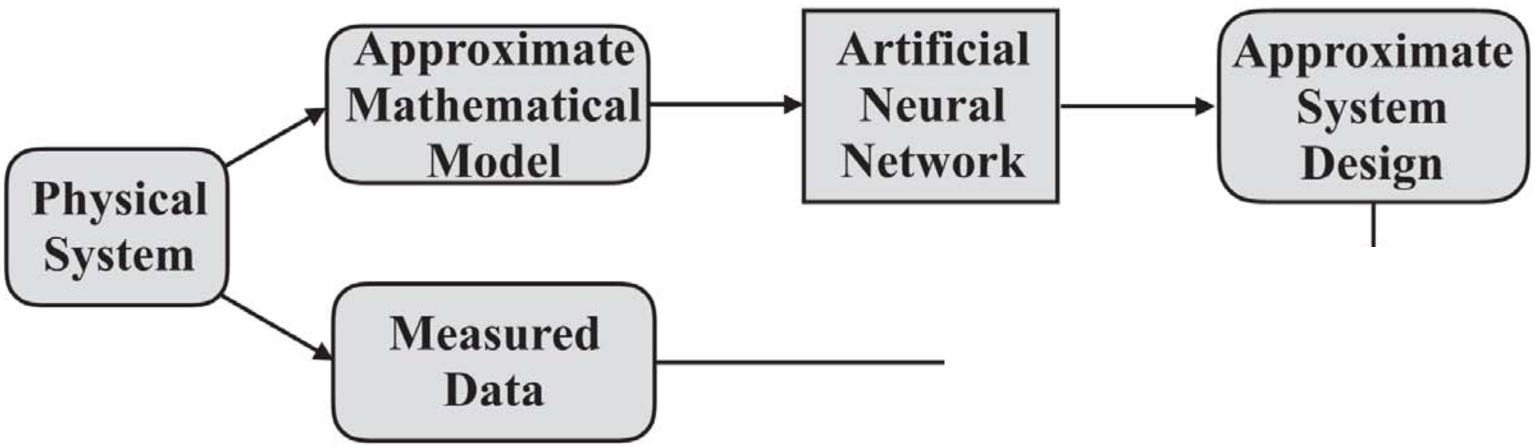

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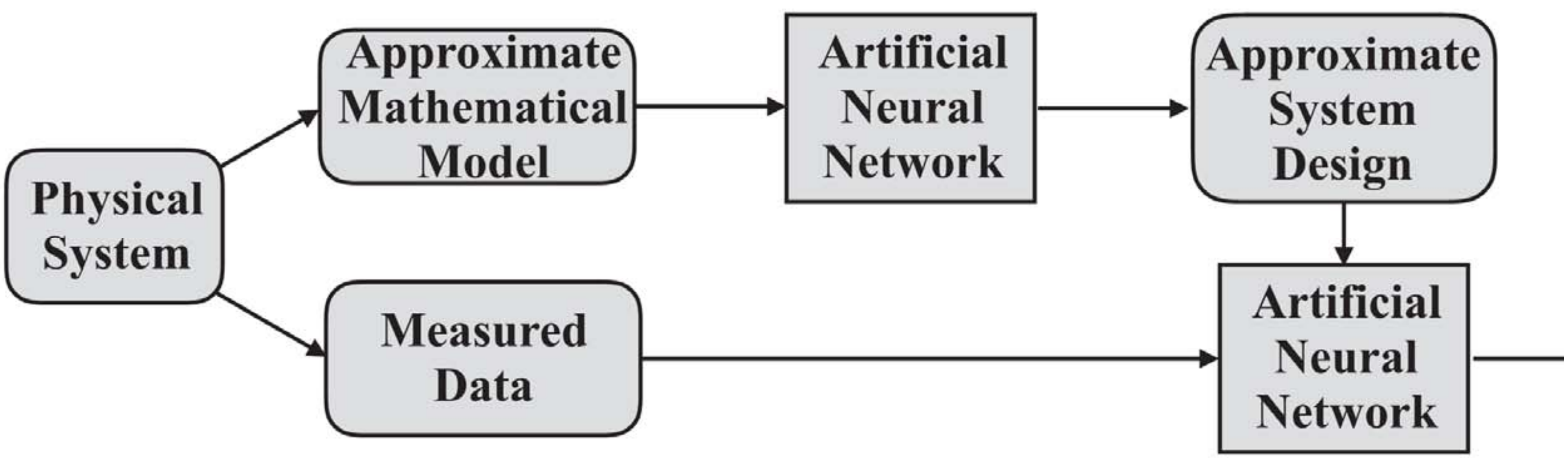

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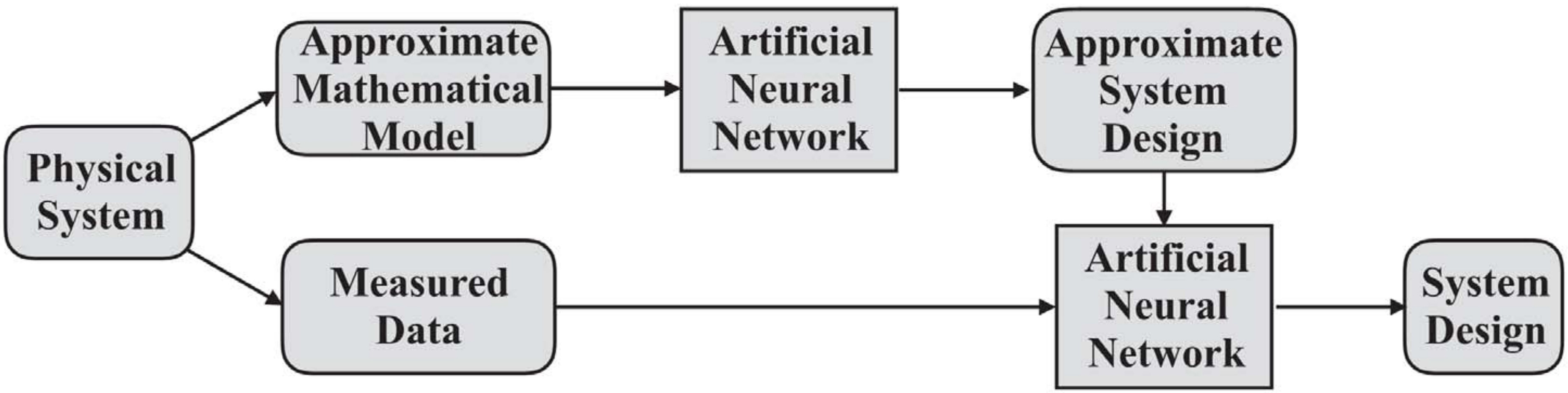
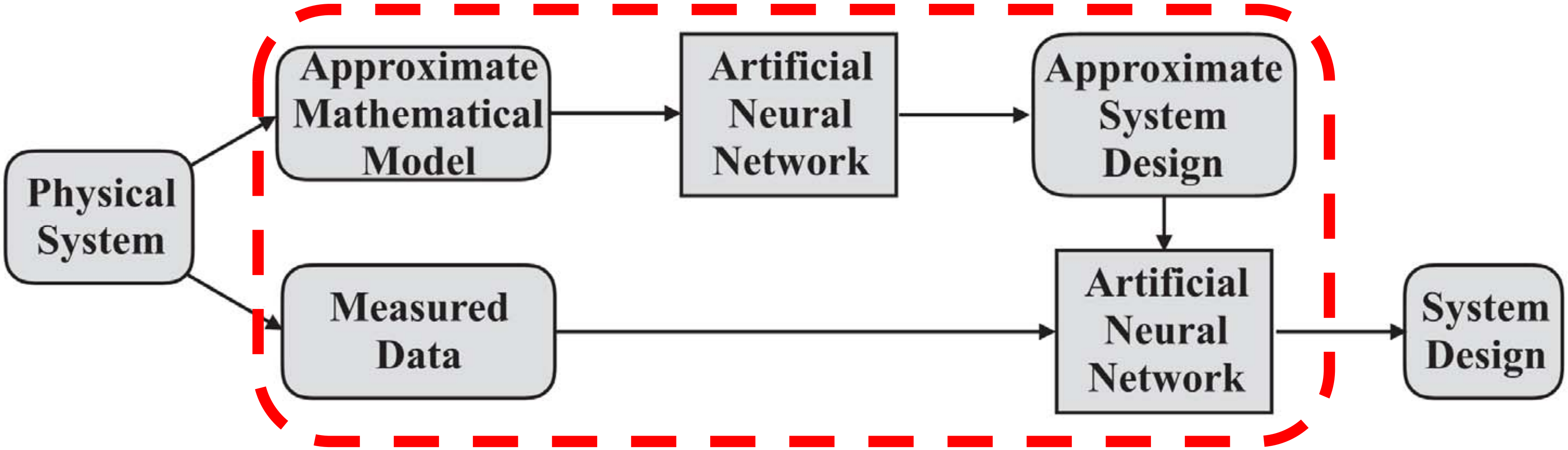


How To Combine Them ?



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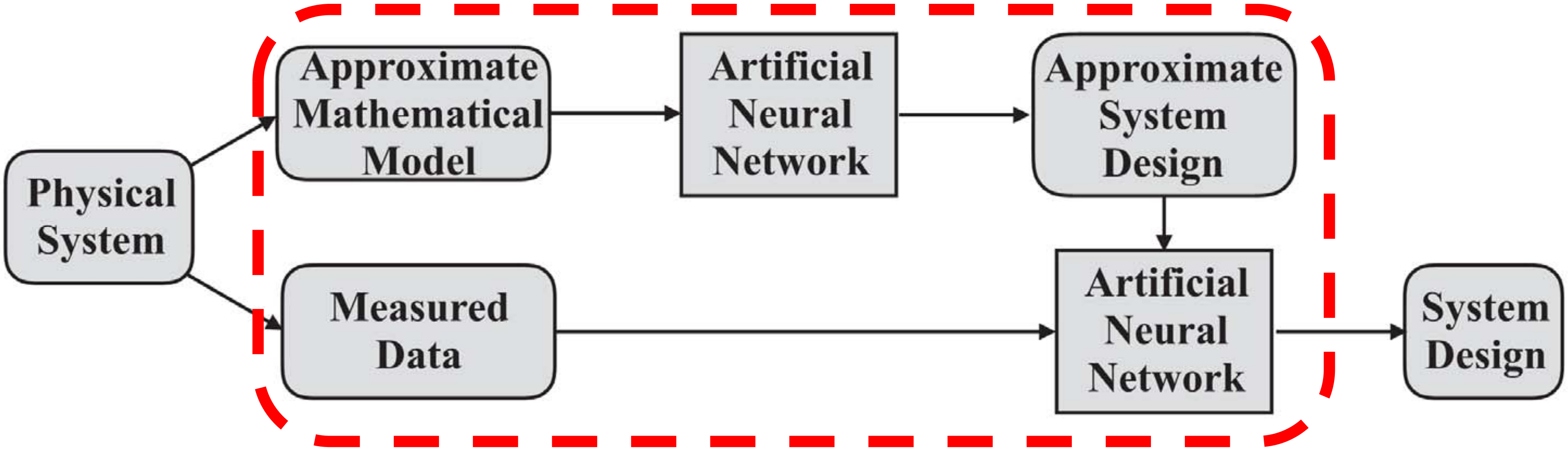
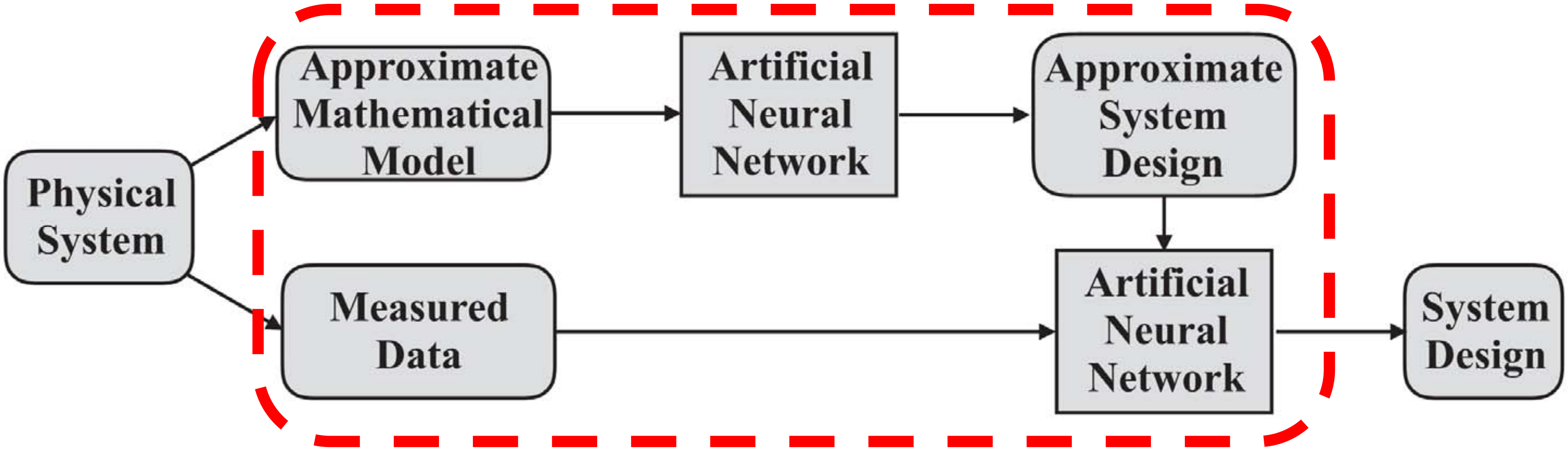
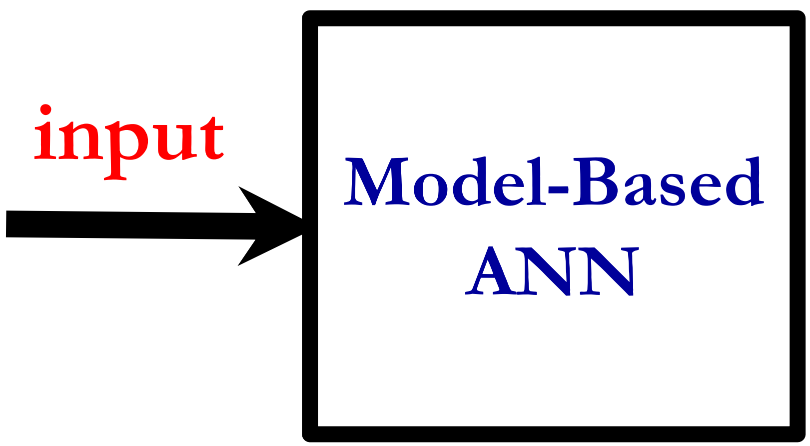


input

How To Combine Them ?





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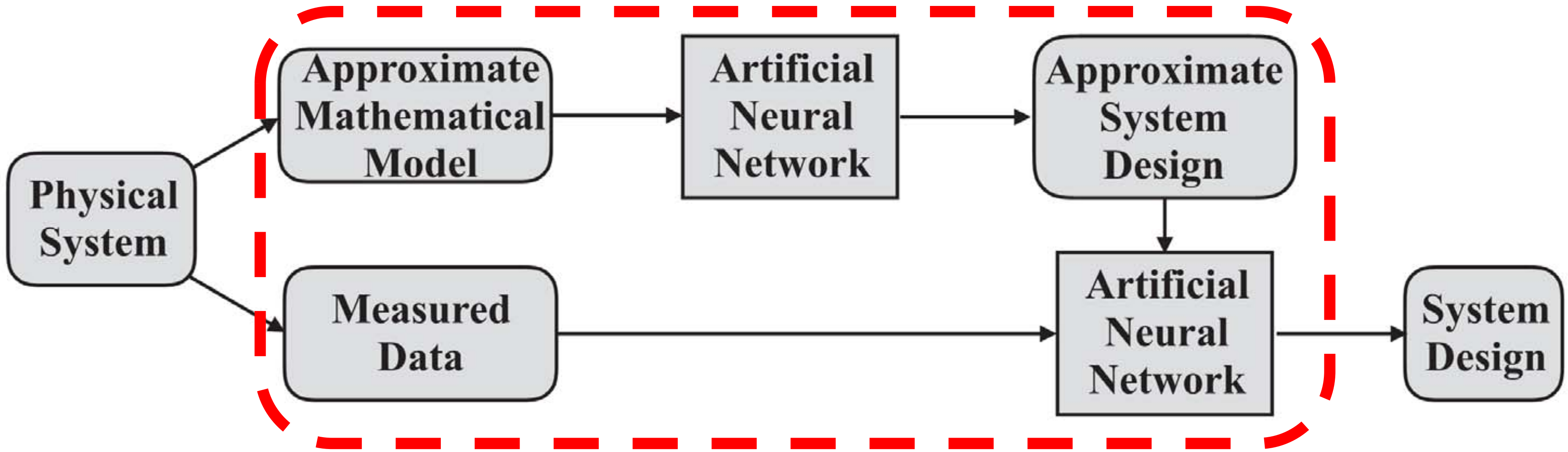

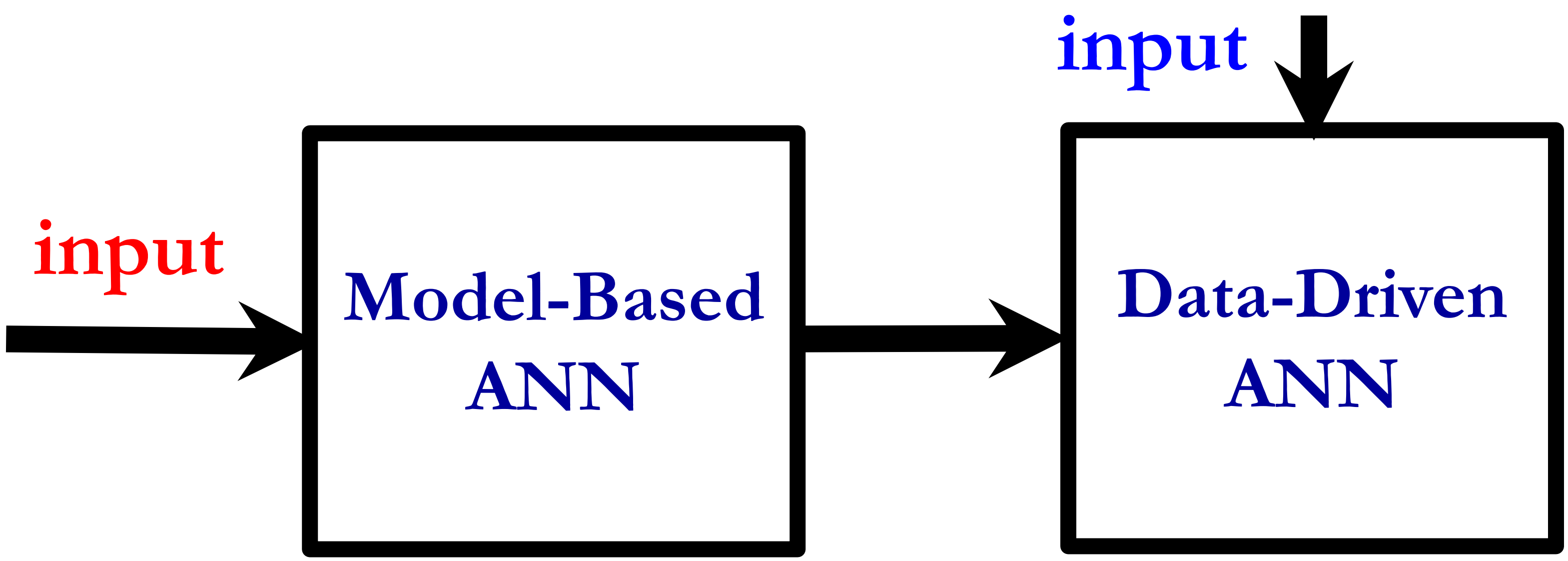

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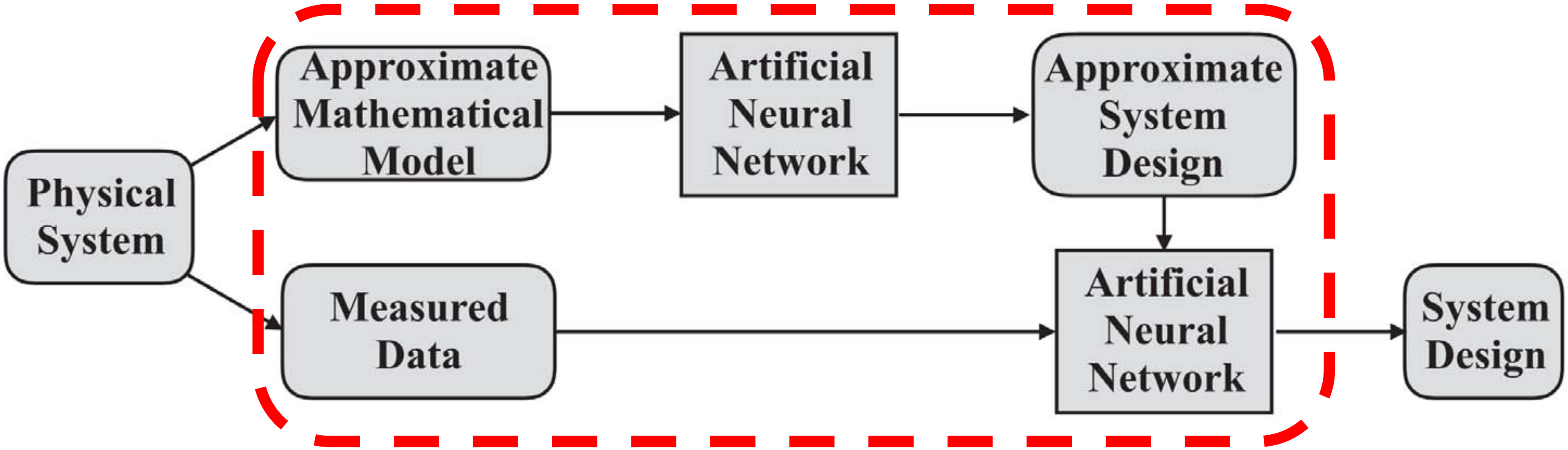
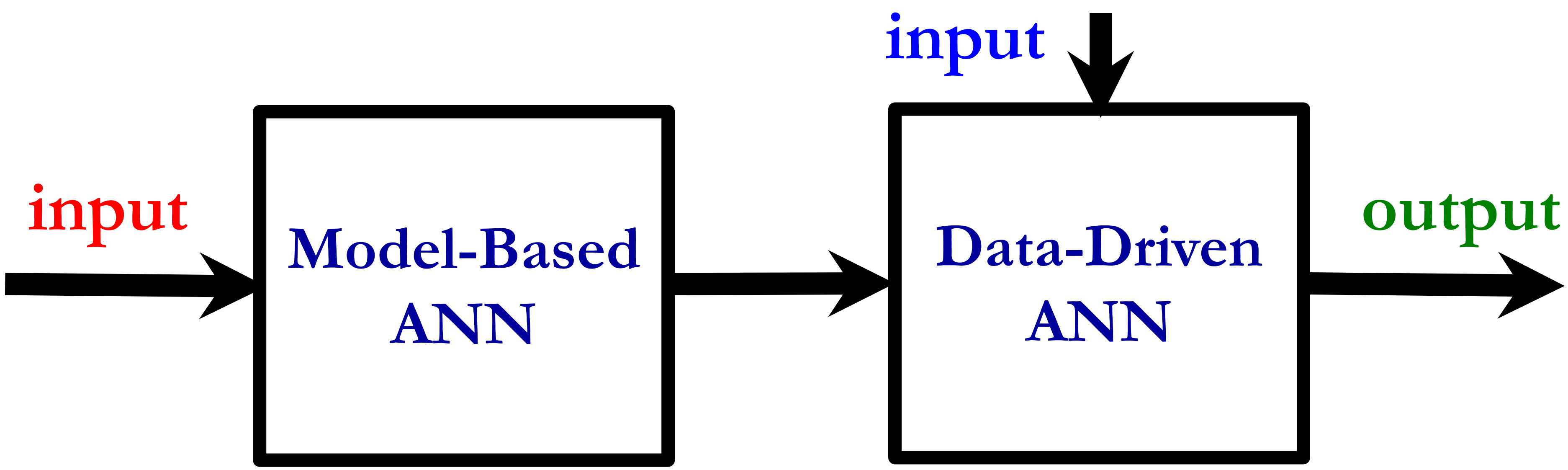
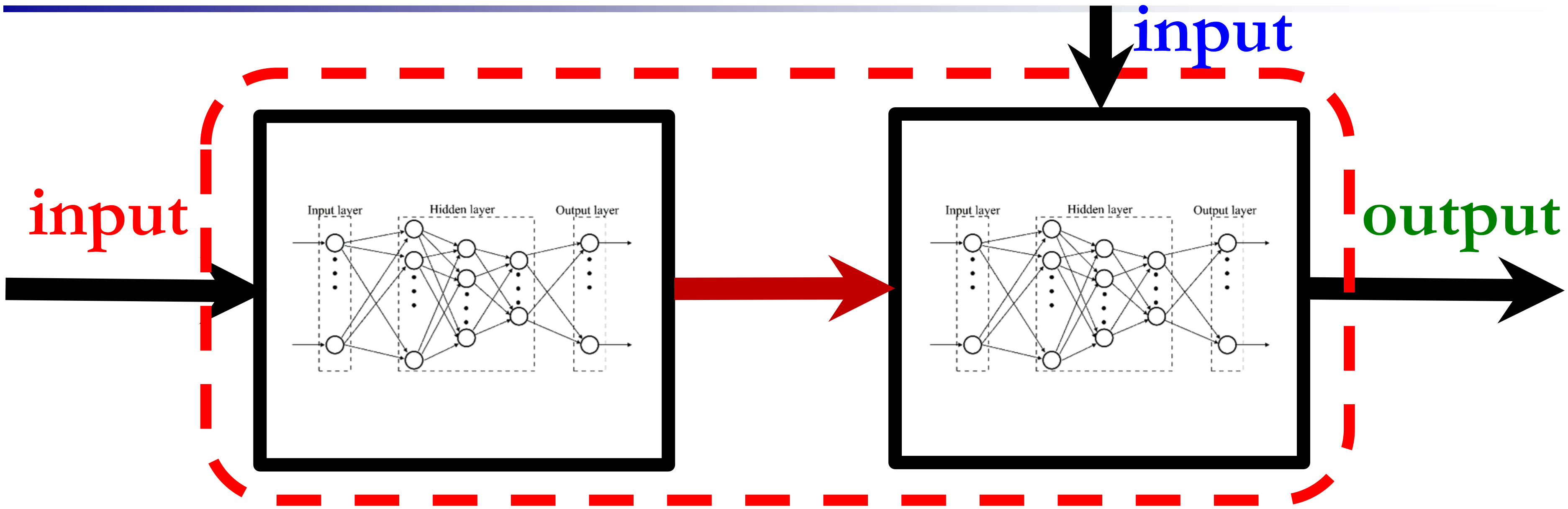




A Simple Example of Transfer



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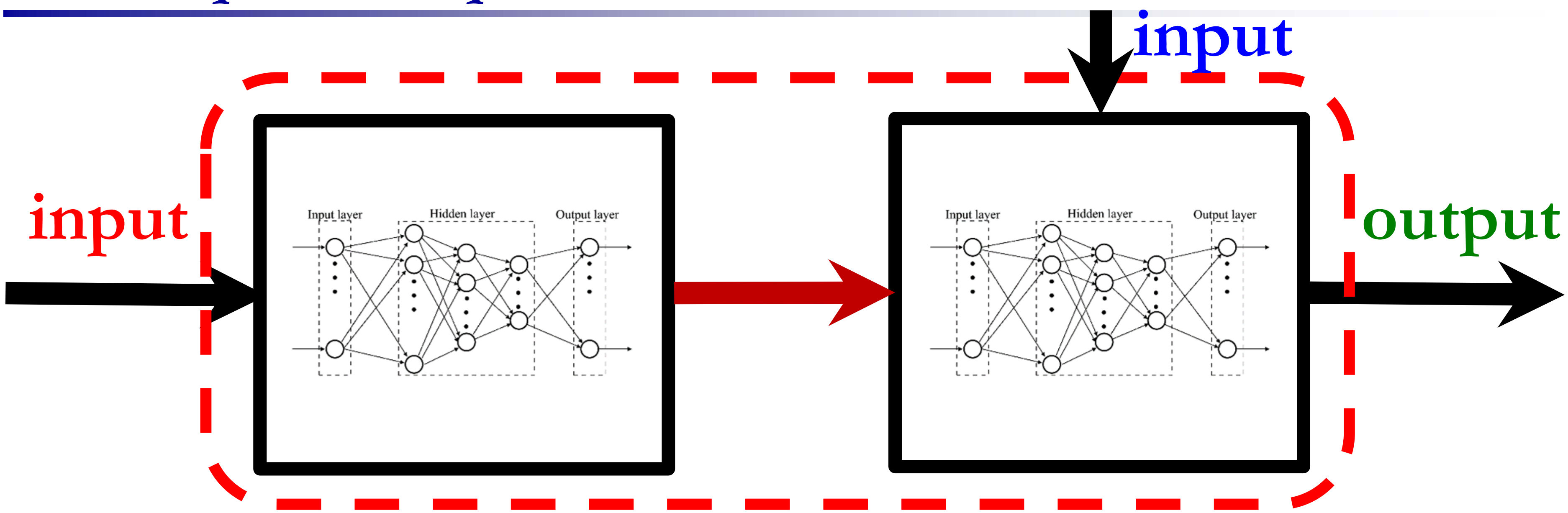

- **Model-based ANN:**
  - Randomly chosen (initial) biases and weights
  - Number of layers and neurons are hyper parameters

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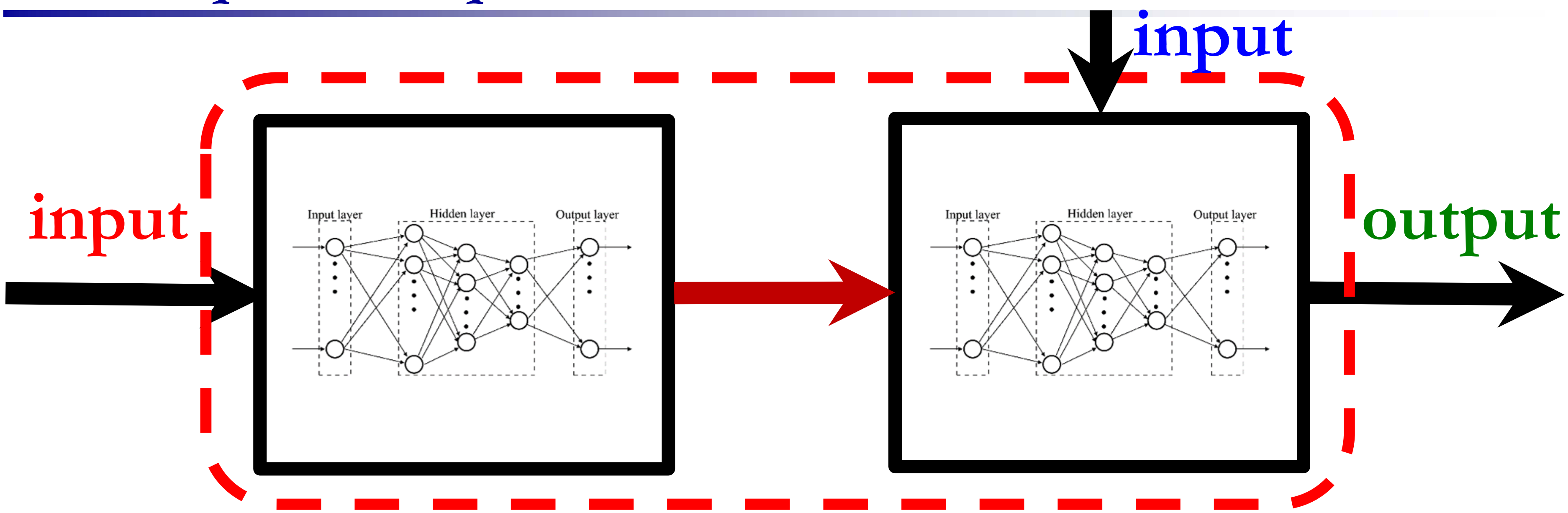
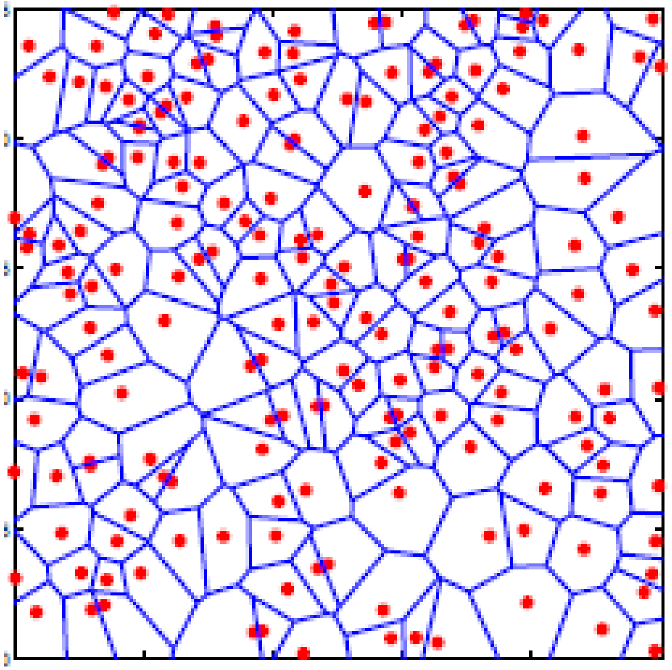


- **Model-based ANN**:
  - Randomly chosen (initial) biases and weights
  - Number of layers and neurons are hyper parameters
- **Data-driven ANN**:
  - Input bias and weights from the model-based ANN
  - Number of layers and neurons is left unchanged

Large-Scale Network Optimization – Example

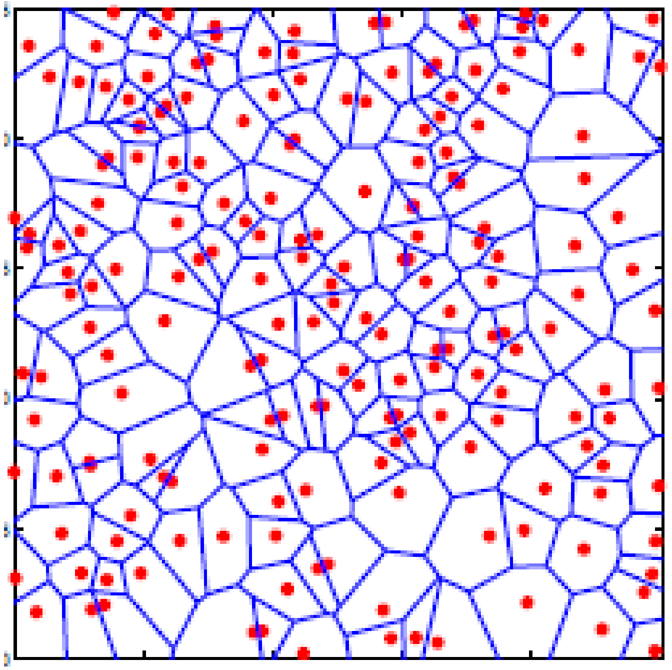
Large-Scale Network Optimization – Example



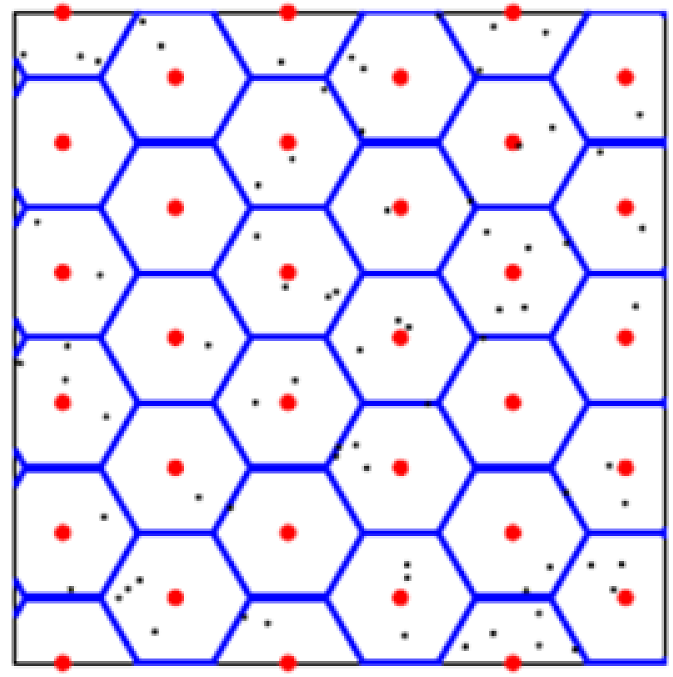
Model

Poisson Point Process

Large-Scale Network Optimization – Example



VS.



Model

Poisson Point Process

Live Data

Lattice Point Process

Approach

Approach

- **Step 1:**
  - **Learning a Poisson Point Process: Learning a model by deep learning**

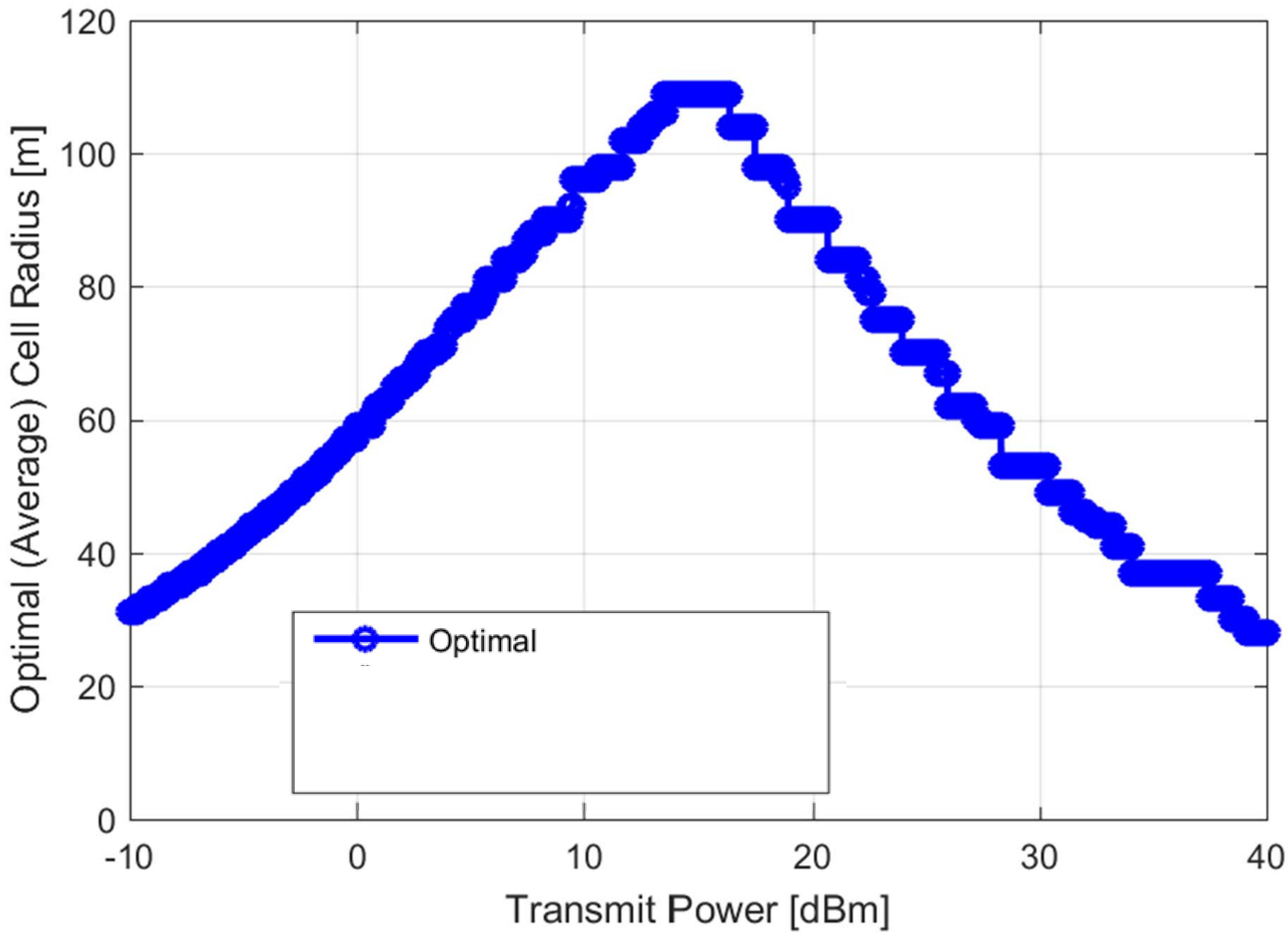
Approach

- **Step 1**:
  - **Learning a Poisson Point Process: Learning a model by deep learning**

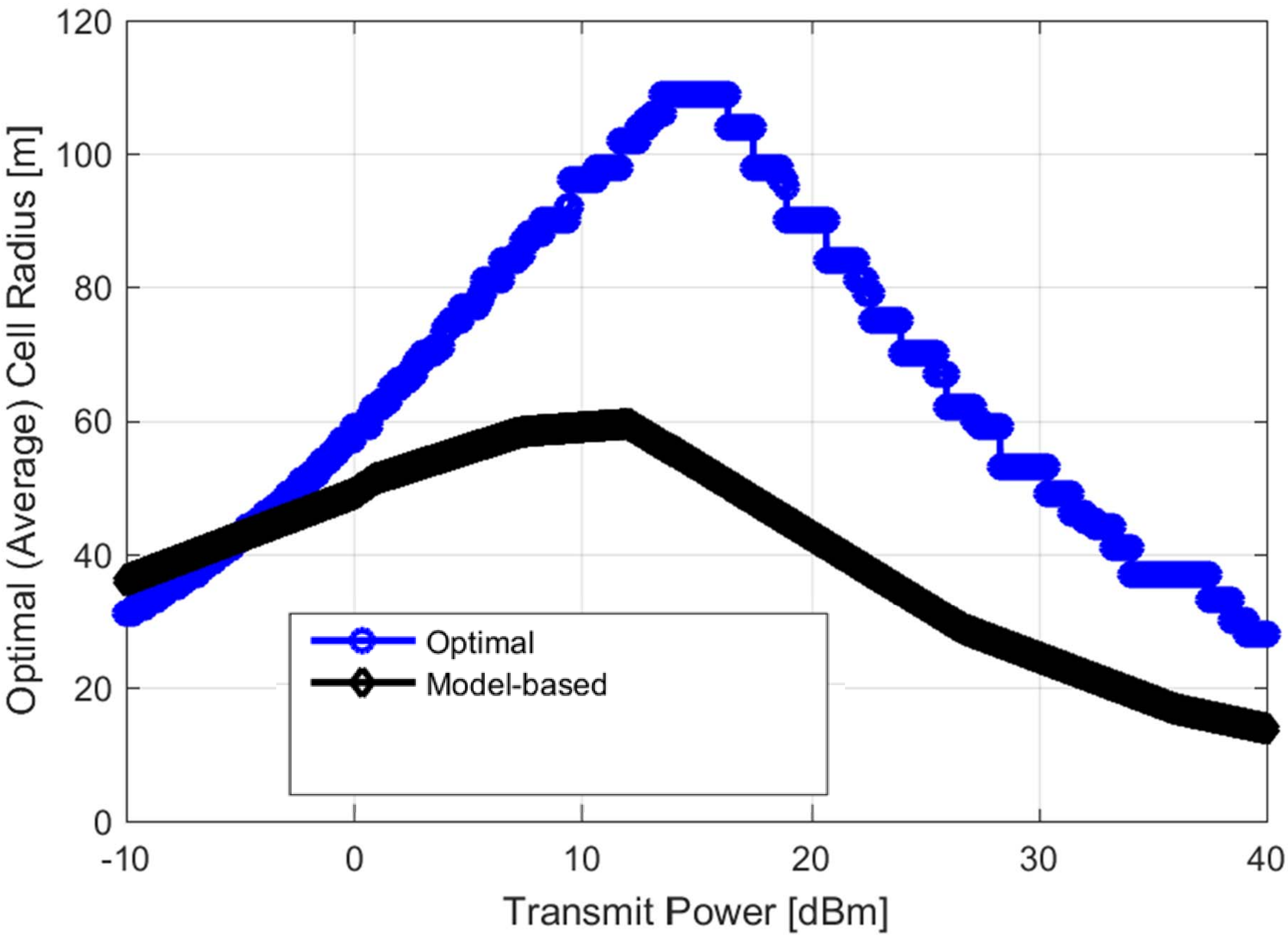
- **Step 2**:
  - **Learning a non-Poisson Point Process: Refining a model via deep transfer learning**

Numerical Example: Modeling vs. Reality

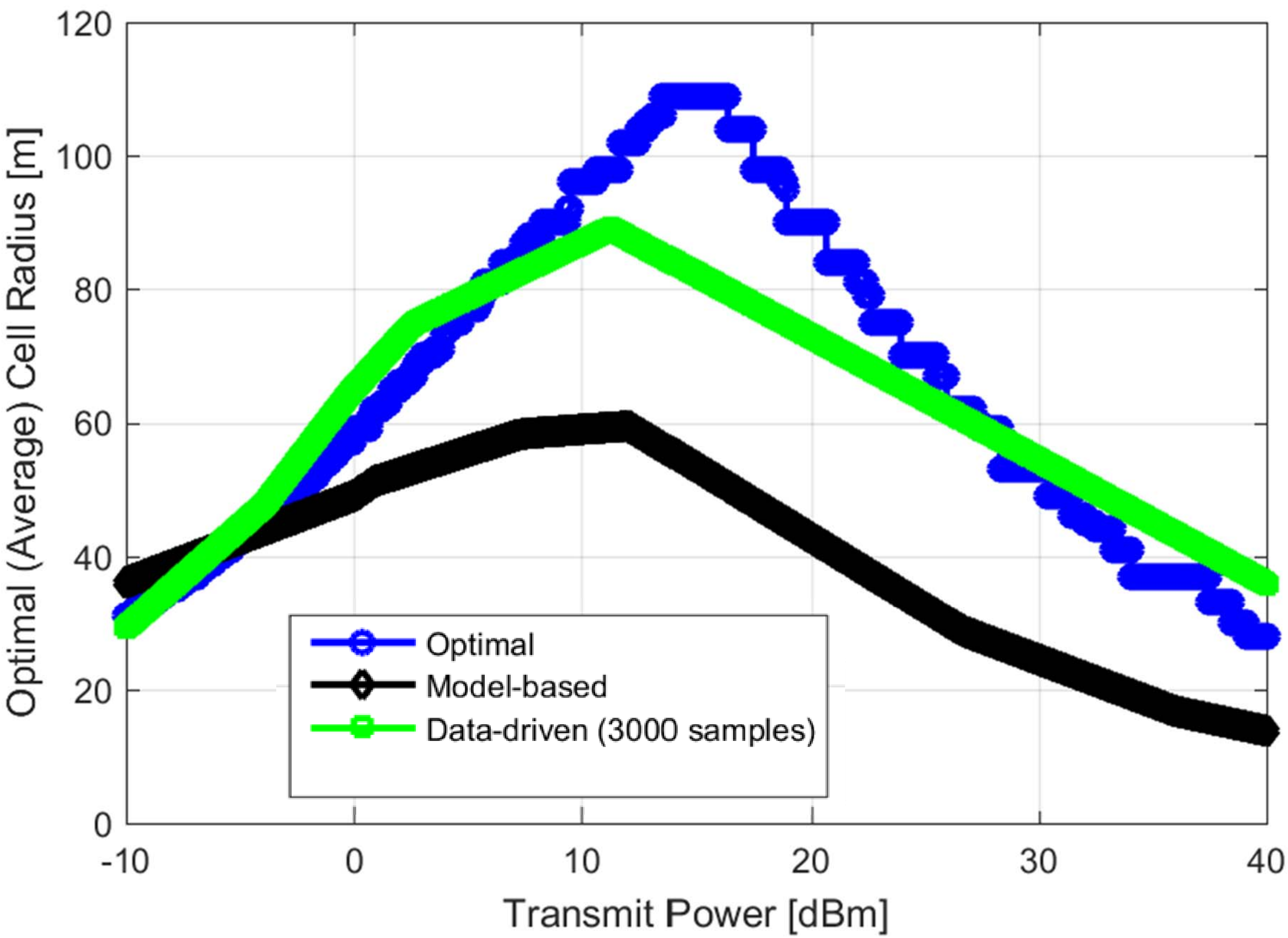
Numerical Example: Modeling vs. Reality (Genie)



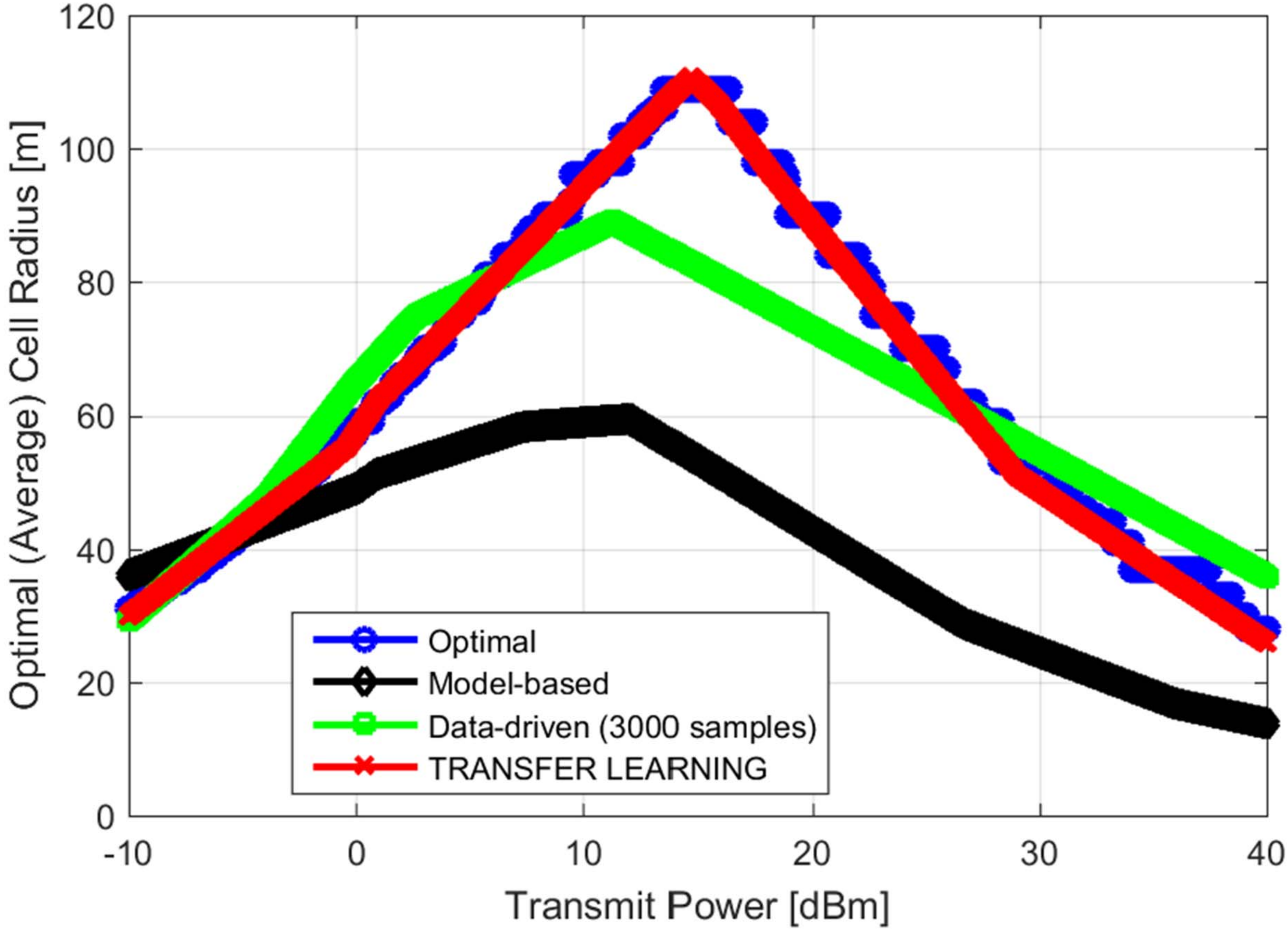
Numerical Example: Modeling vs. Reality (Model)



Numerical Example: Modeling vs. Reality (Few Data)



Numerical Example: Modeling vs. Reality (Transfer)



… Closing Remarks …
(Main Takes)

Programming the Environment: Towards Wireless 2.0

Di Renzo *et al. EURASIP Journal on Wireless Communications and Networking* (2019) 2019:129
https://doi.org/10.1186/s13638-019-1438-9

EURASIP Journal on Wireless Communications and Networking

REVIEW **Open Access**

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Smart radio environments empowered by reconfigurable AI meta-surfaces: an idea whose time has come

Marco Di Renzo[1*], Merouane Debbah[2], Dinh-Thuy Phan-Huy[3], Alessio Zappone[4], Mohamed-Slim Alouini[5], Chau Yuen[6], Vincenzo Sciancalepore[7], George C. Alexandropoulos[8], Jakob Hoydis[9], Haris Gacanin[10], Julien de Rosny, Ahcene Bounceur[12], Geoffroy Lerosey[13] and Mathias Fink[11]

Abstract

Future wireless networks are expected to constitute a distributed intelligent wireless communications, sensing, and computing platform, which will have the challenging requirement of interconnecting the physical and digital worlds in a seamless and sustainable manner. Currently, two main factors prevent wireless network operators from building such networks: (1) the lack of control of the wireless environment, whose impact on the radio waves cannot be customized, and (2) the current operation of wireless radios, which consume a lot of power because new signals are generated whenever data has to be transmitted. In this paper, we challenge the usual "more data needs more power and emission of radio waves" status quo, and motivate that future wireless networks necessitate a smart radio environment: a transformative wireless concept, where the environmental objects are coated with artificial thin films of electromagnetic and reconfigurable material (that are referred to as reconfigurable intelligent meta-surfaces), which are capable of sensing the environment and of applying customized transformations to the radio waves. Smart radio environments have the potential to provide future wireless networks with uninterrupted wireless connectivity,

Wireless 2.0: Towards an Intelligent Radio Environment Empowered by Reconfigurable Meta-Surfaces and Artificial Intelligence

Haris Gacanin and Marco Di Renzo

***Abstract*—We introduce "Wireless 2.0": The future generation of wireless communication networks, where the radio environment becomes controllable, programmable, and intelligent by leveraging the emerging technologies of reconfigurable meta-surfaces and artificial intelligence (AI). This paper, in particular, puts the emphasis on AI-based computational methods and commence with an overview of the concept of intelligent radio environments based on reconfigurable meta-surfaces. Later we elaborate on data management aspects, the requirements of supervised learning by examples, and the paradigm of reinforcement learning (RL) to learn by acting. Finally, we highlight numerous open challenges and research directions.**

wireless communication systems remain extremely inefficient due to the constraints imposed by the radio environment per se. A typical base station, for example, transmits radio waves of the order of magnitude of Watts while a typical user equipment detects signals of the order of magnitude of μWatts. The rest of the energy is either dissipated over the channel or is a source of interference for other network elements.

These fundamental limitations are challenged by recent research on intelligent radio environments (IREs) [1]. In IREs, the technology enablers of reconfigurable meta-surfaces

H. Gacanin and M. Di Renzo, Vehicular Technol. Mag., arXiv:2002.11040

Were Are We ?

Reconfigurable Intelligent Metasurfaces

Were Are We ?

1G

Uniform Metasurface
(Homogenization of periodic)

2000-2010

2G

Non- Uniform Metasurface
(Space - variable)

2010-2020

- ❑ **Extending the range of applicability**
  - ❑ **Ultrawideband**
  - ❑ **Shaped beams**
  - ❑ **Multibeam**
  - ❑ **Multifrequency**

3G

Reconfigurable Metasurface
(Space-time variable)

2020-2030

- ❑ **Reconfigurability by switches**
- ❑ **Reconfigurability by tunable material**
- ❑ **Topological Metasurface**
- ❑ **Smart metasurfaces beyond 5G**

Smart space-time Metasurfaces can be the key-future technology for smart environment “beyond 5G”

Wireless 2.0: 6G Wireless + 3G Metasurfaces (JSAC)

Smart Radio Environments Empowered by Reconfigurable Intelligent Surfaces: How it Works, State of Research, and Road Ahead

Marco Di Renzo, *Fellow, IEEE*, Alessio Zappone, *Senior Member, IEEE*, Merouane Debbah, *Fellow, IEEE*, Mohamed-Slim Alouini, *Fellow, IEEE*, Chau Yuen, *Senior Member, IEEE*, Julien de Rosny, and Sergei Tretyakov, *Fellow, IEEE*

***Abstract*—Reconfigurable intelligent surfaces (RISs) are an emerging transmission technology for application to wireless communications. RISs can be realized in different ways, which include (i) large arrays of inexpensive antennas that are usually spaced half of the wavelength apart; and (ii) metamaterial-based planar or conformal large surfaces whose scattering elements have sizes and inter-distances much smaller than the wavelength. Compared with other transmission technologies, e.g., phased arrays, multi-antenna transmitters, and relays, RISs require the largest number of scattering elements, but each of them needs to be backed by the fewest and least costly components. Also, no power amplifiers are usually needed. For these reasons, RISs constitute a promising software-defined architecture that can be realized at reduced cost, size, weight, and power (C-SWaP design), and are regarded as an enabling technology for realizing the emerging concept of smart radio environments (SREs).**

In this paper, we (i) introduce the emerging research field of RIS-empowered SREs; (ii) overview the most suitable applications of RISs in wireless networks; (iii) present an electromagnetic-based communication-theoretic framework for analyzing and optimizing metamaterial-based RISs; (iv) provide a comprehensive overview of the current state of research; and (v) discuss the most important research issues to tackle.

Owing to the interdisciplinary essence of RIS-empowered SREs, finally, we put forth the need of reconciling and reuniting C. E. Shannon's mathematical theory of communication with G. Green's and J. C. Maxwell's mathematical theories of electromagnetism for appropriately modeling, analyzing, optimizing, and deploying future wireless networks empowered by RISs.

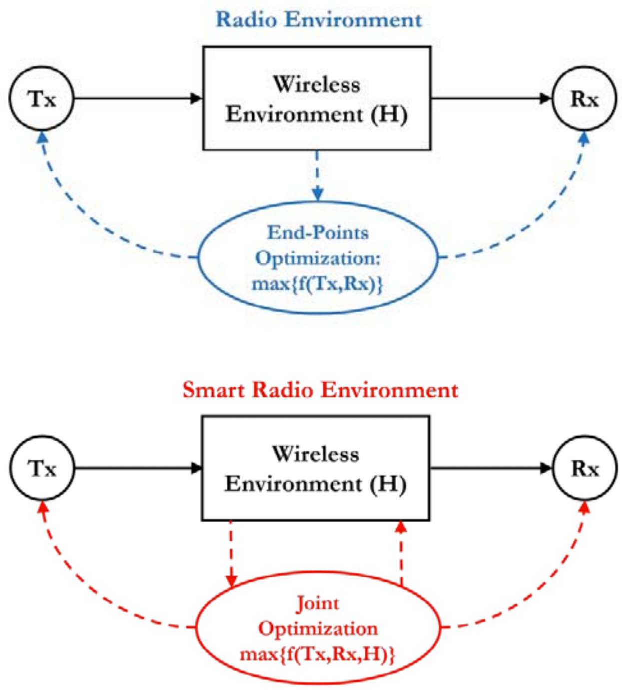
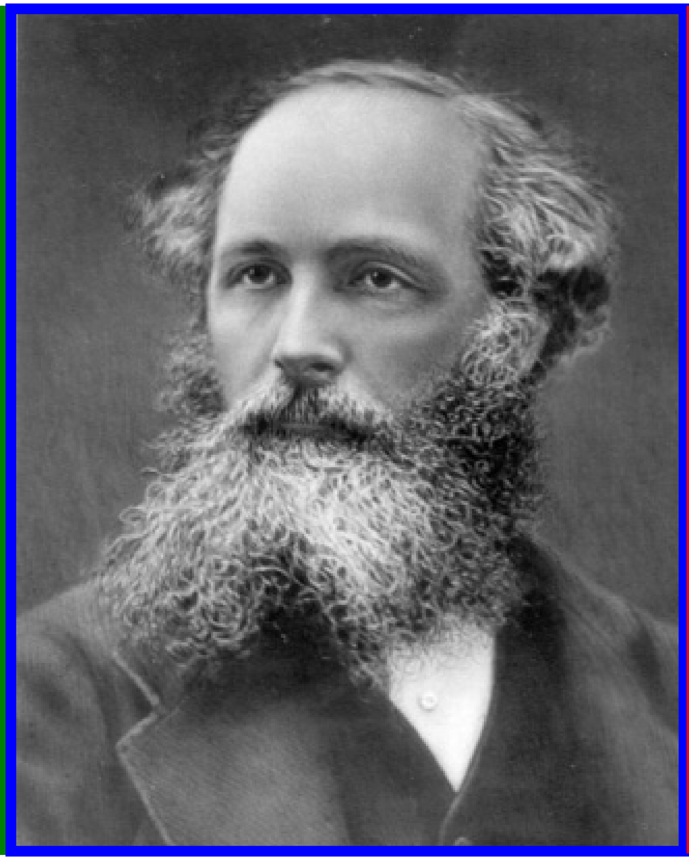
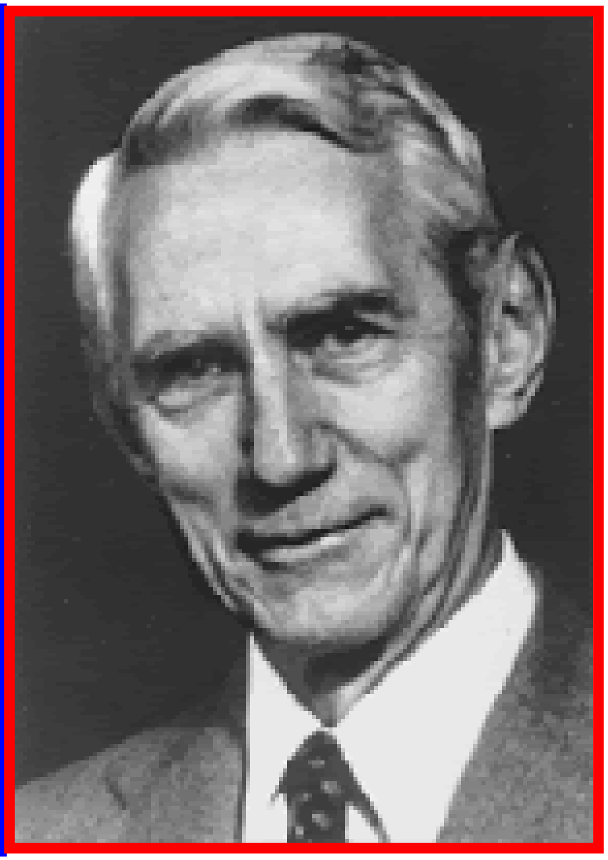


Fig. 1: Radio environments vs. smart radio environments.

The Road Ahead: Reconciling COM, SP, IT, EM, …





G. Green, "An Essay on the Application of Mathematical Analysis to the Theories of Electricity and Magnetism", 1828.

J. C. Maxwell, "A Dynamical Theory of the Electromagnetic Field", 1865.

C. E. Shannon, "A (The) Mathematical Theory of Communication", 1948.

From Model-or-Data to Model-and-Data Design…

Wireless Networks Design in the Era of Deep Learning: Model-Based, AI-Based, or Both?

Alessio Zappone, *Senior Member, IEEE*, Marco Di Renzo, *Senior Member, IEEE*, Mérouane Debbah, *Fellow, IEEE*

(Invited Paper)

https://arxiv.org/abs/1902.02647

Abstract—**This work addresses the use of emerging data-driven techniques based on deep learning and artificial neural networks in future wireless communication networks. In particular, a key point that will be made and supported throughout the work is that data-driven approaches should not replace traditional design techniques based on mathematical models. On the contrary, despite being seemingly mutually exclusive, there is much to be gained by merging data-driven and model-based approaches.**

To begin with, a detailed presentation is given for the reasons why deep learning based on artificial neural networks will be an indispensable tool for the design and operation of future wireless communications networks, as well as a description of the recent technological advances that make deep learning practically viable for wireless applications. Our vision of how artificial neural networks should be integrated into the architecture of future wireless communication networks is presented, explaining the main areas where deep learning provides a decisive advantage over traditional approaches.

Afterwards, a thorough description of deep learning methodologies is provided, starting with presenting the general machine

I. Introduction and Vision

All past and present generations of wireless communication networks are based on mathematical *models*, that are either derived from theoretical considerations, or from field measurement campaigns. Mathematical models are at the heart of all phases of network design, describing in quantitative terms the effect that each system component has on the overall performance. Mathematical models are used for initial network planning and deployment, for network resource management, as well as for network maintenance and control. Based on underlying models, infrastructure nodes are statically deployed to cover and manage fixed geographical areas, and traditional optimization theory is used to optimize the network performance through the centralized allocation of the available system resources. However, this traditional approach to network design has at least two drawbacks:

The Road Ahead: Reconciling COM, SP, IT, EM, & ML

RIS @ IEEE-COMSOC

Wireless Communications Technical Committee, Special Interest Group: "Reconfigurable Intelligent Surfaces for Smart Radio Environments (RISE)"

Signal Processing and Computing for Communications Technical Committee, Special Interest Group: "REconFigurabLE Intelligent Surfaces for Signal Processing & CommunicatIONS (REFLECTIONS)"

Emerging Technology Initiative (ETI): "Reconfigurable Intelligent Surfaces"

Best Readings, "Reconfigurable Intelligent Surfaces"

Further Information @ Google Scholar

Marco Di Renzo

FOLLOW

CNRS Research Director - CentraleSupelec, Paris-Saclay University
Verified email at l2s.centralesupelec.fr - Homepage

Wireless Communications Communication Theory Stochastic Geometry Spatial Modulation RIS

TITLE	CITED BY	YEAR
Stochastic Learning-Based Robust Beamforming Design for RIS-Aided Millimeter-Wave Systems in the Presence of Random Blockages G Zhou, C Pan, H Ren, K Wang, M Elkashlan, M Di Renzo arXiv preprint arXiv:2009.09716		2020
End-to-End Mutual-Coupling-Aware Communication Model for Reconfigurable Intelligent Surfaces: An Electromagnetic-Compliant Approach Based on Mutual Impedances G Gradoni, M Di Renzo arXiv preprint arXiv:2009.02694		2020
Single-RF MIMO: From Spatial Modulation to Metasurface-Based Modulation Q Li, M Wen, M Di Renzo arXiv preprint arXiv:2009.00789		2020
Ergodic Secrecy Capacity of RIS-Assisted Communication Systems in the Presence of Discrete Phase Shifts and Multiple Eavesdroppers P Xu, G Chen, G Pan, M Di Renzo arXiv preprint arXiv:2009.00517		2020
Robust Secure UAV Communications with the Aid of Reconfigurable Intelligent Surfaces L Sixian, D Bin, M Di Renzo, T Meixia, Y Xiaojun arXiv preprint arXiv:2008.09404		2020
Achievable Rate Optimization for MIMO Systems with Reconfigurable Intelligent Surfaces NS Perović, LN Tran, M Di Renzo, MF Flanagan arXiv preprint arXiv:2008.09563		2020
Robust probabilistic-constrained optimization for IRS-aided MISO communication systems TA Le, T Van Chien, M Di Renzo IEEE Wireless Communications Letters	1	2020

Thank You For Having Me… Appreciated…

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- **November 1st, 2019 – October 31st, 2022**

A collaborative research project on RISs & AI

H2020-2018-2020, ICT

ARIADNE

Marco Di Renzo, Ph.D., H.D.R.

Directeur de Recherche CNRS (CNRS Professor)

Highly Cited Researcher, Web of Science

IEEE Fellow, IEEE Communications Society

Editor-in-Chief, IEEE Communications Letters

Distinguished Lecturer, IEEE Communications Society

Distinguished Lecturer, IEEE Vehicular Technol. Society

Nokia Foundation Visiting Professor, Aalto Univ., Finland

Paris-Saclay University

Laboratory of Signals and Systems (L2S)

CNRS and CentraleSupelec

E-Mail: marco.direnzo@centralesupelec.fr

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