Modern Wireless Network Term Paper:

Deep learning for energy-efficient beyond 5G networks

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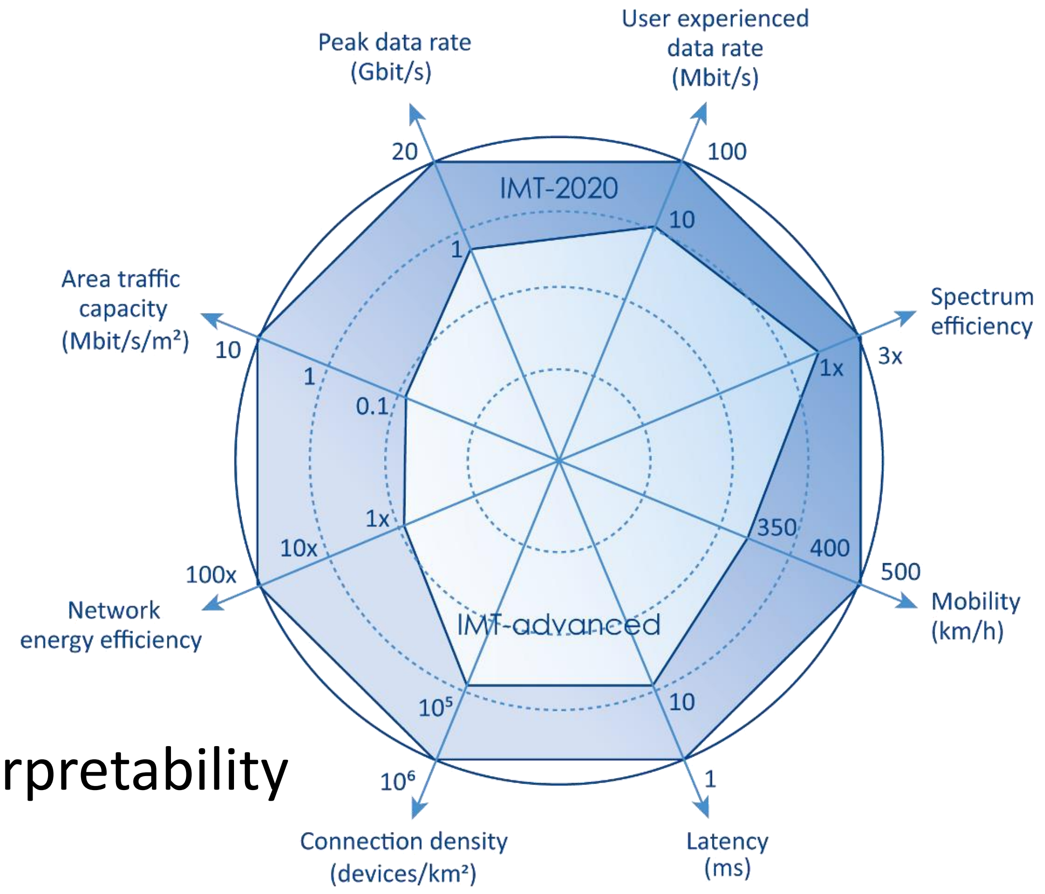
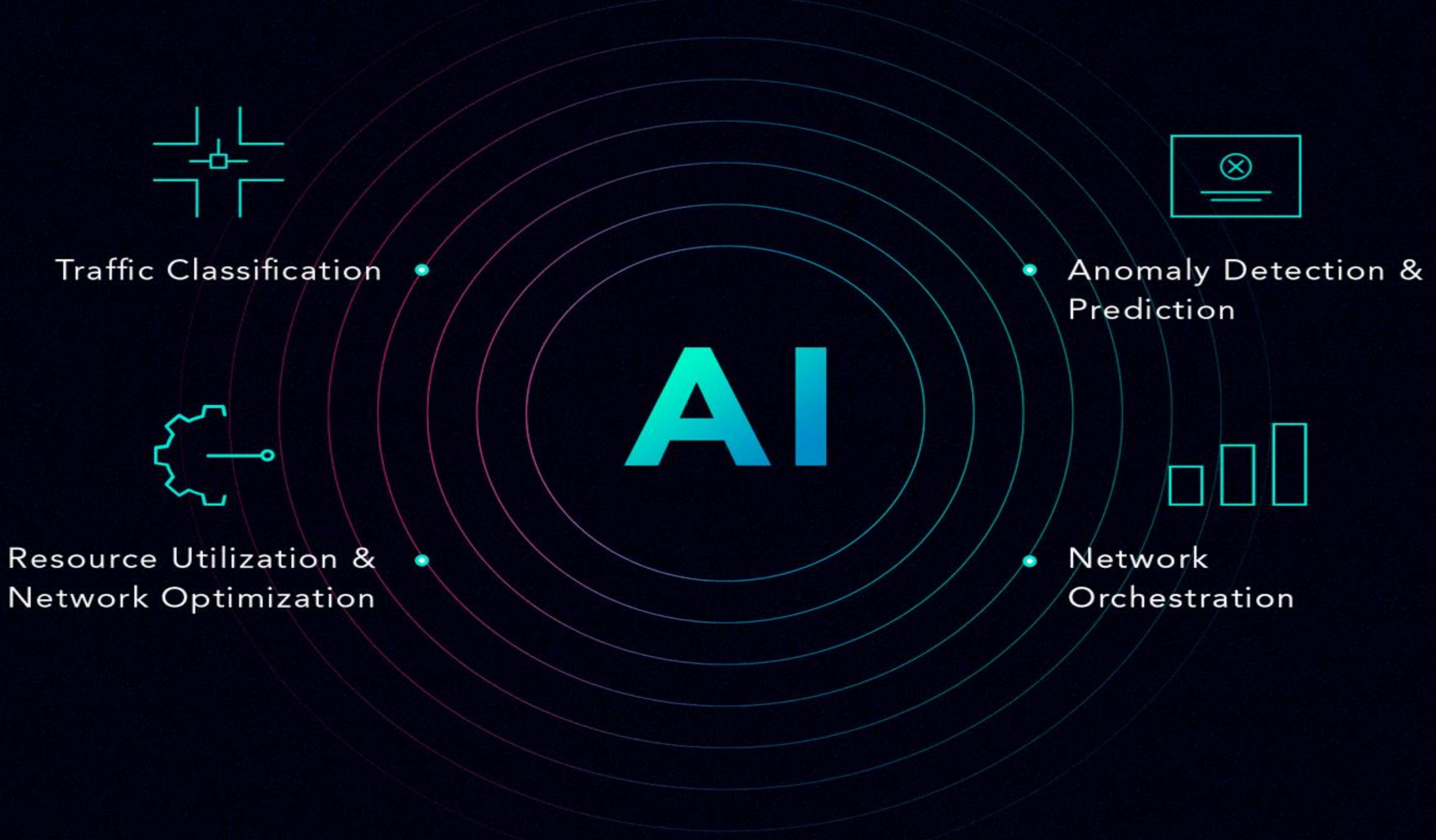
Introduction

- ❖ mathematical models & complexity crunch
- ❖ Artificial Intelligence
- ❖ Integration of conventional approach and AI

- ❖ Learning alongside solving
- ❖ Understanding policy regardless of interpretability

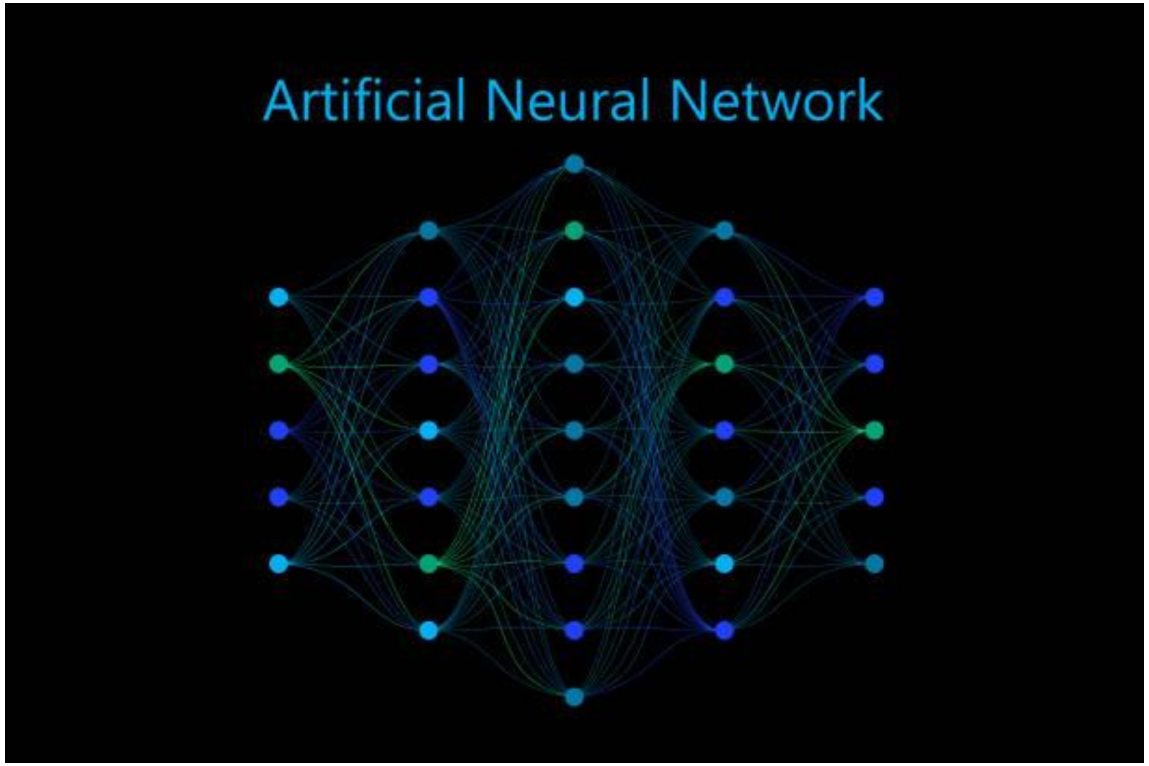


AREAS OF AI IMPACT IN TELCO

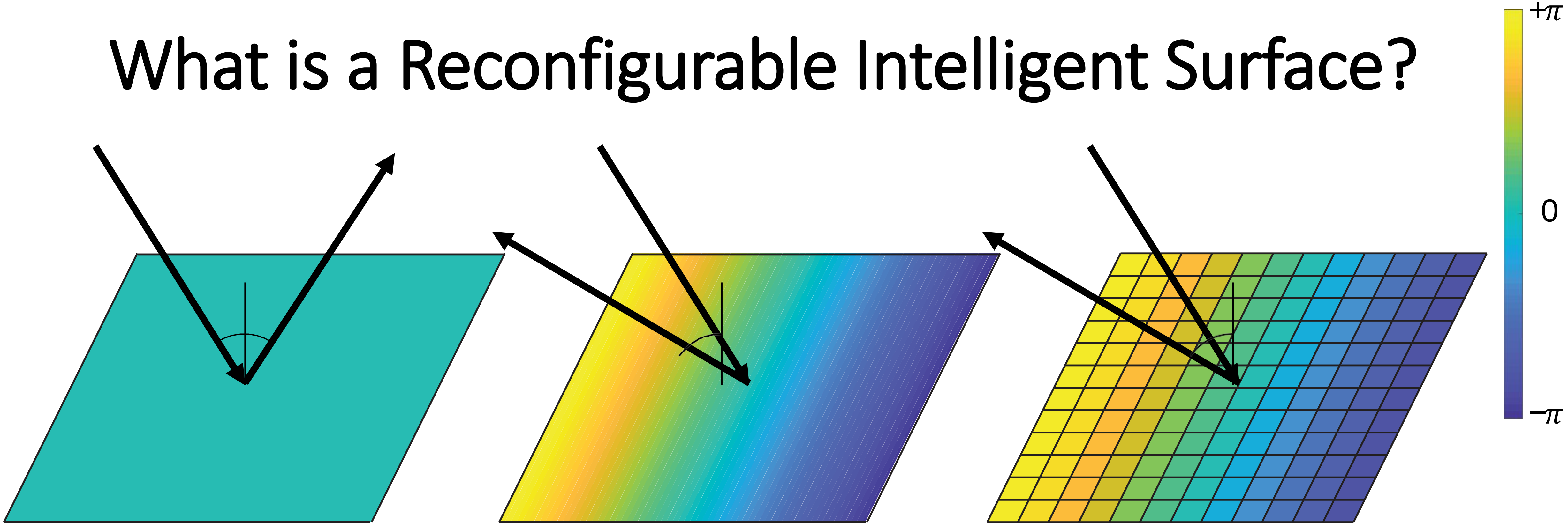


Artificial Neural Network

- ❖ Data acquisition
- ❖ ANNs deployment into communication networks



What is a Reconfigurable Intelligent Surface?



Metal plate

(Snell's law)

Ideal Metasurface

(Generalized Snell's law)

Practical Metasurface

(Discretization)

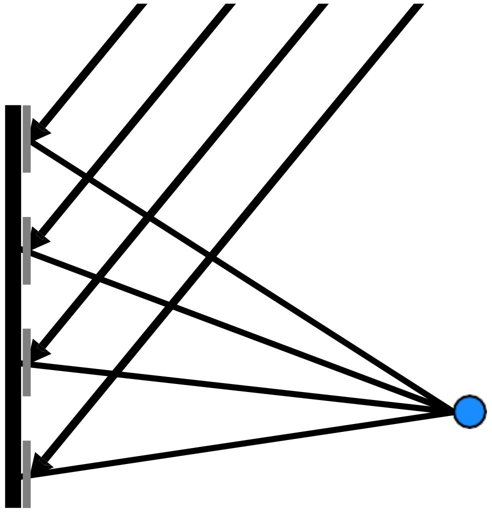
Constant surface impedance

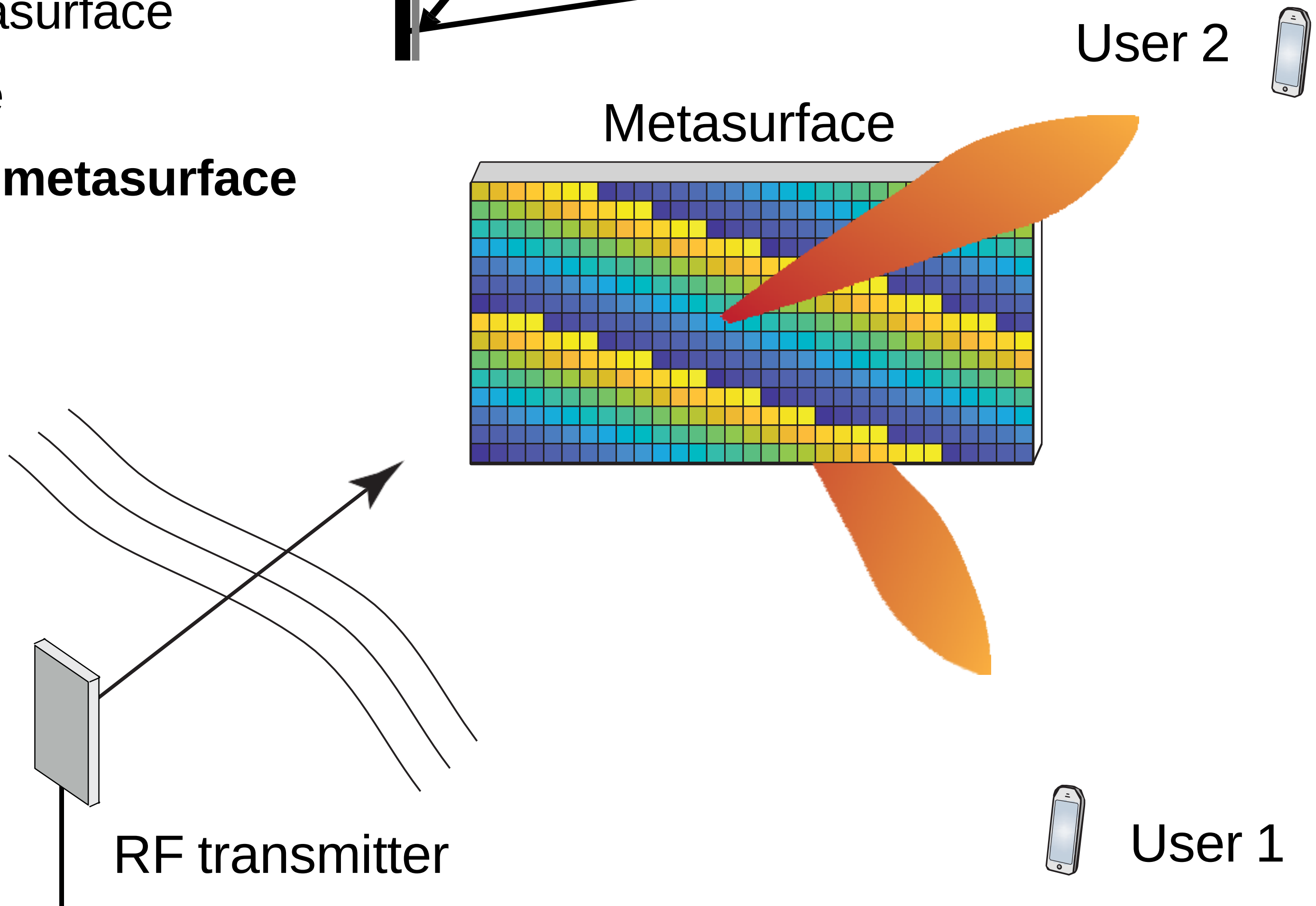
Altering surface impedance to phase-shift reflection

Approximation with discrete elements, e.g., $\frac{!}{''} \times \frac{!}{''}$

Evolution of the Concept

1. Fixed reflectarray (1960s)
2. Reconfigurable reflectarray/metasurface
3. Software-controlled metasurface
4. **Real-time software-controlled metasurface**





Exciting Idea: Intelligent Propagation Environments

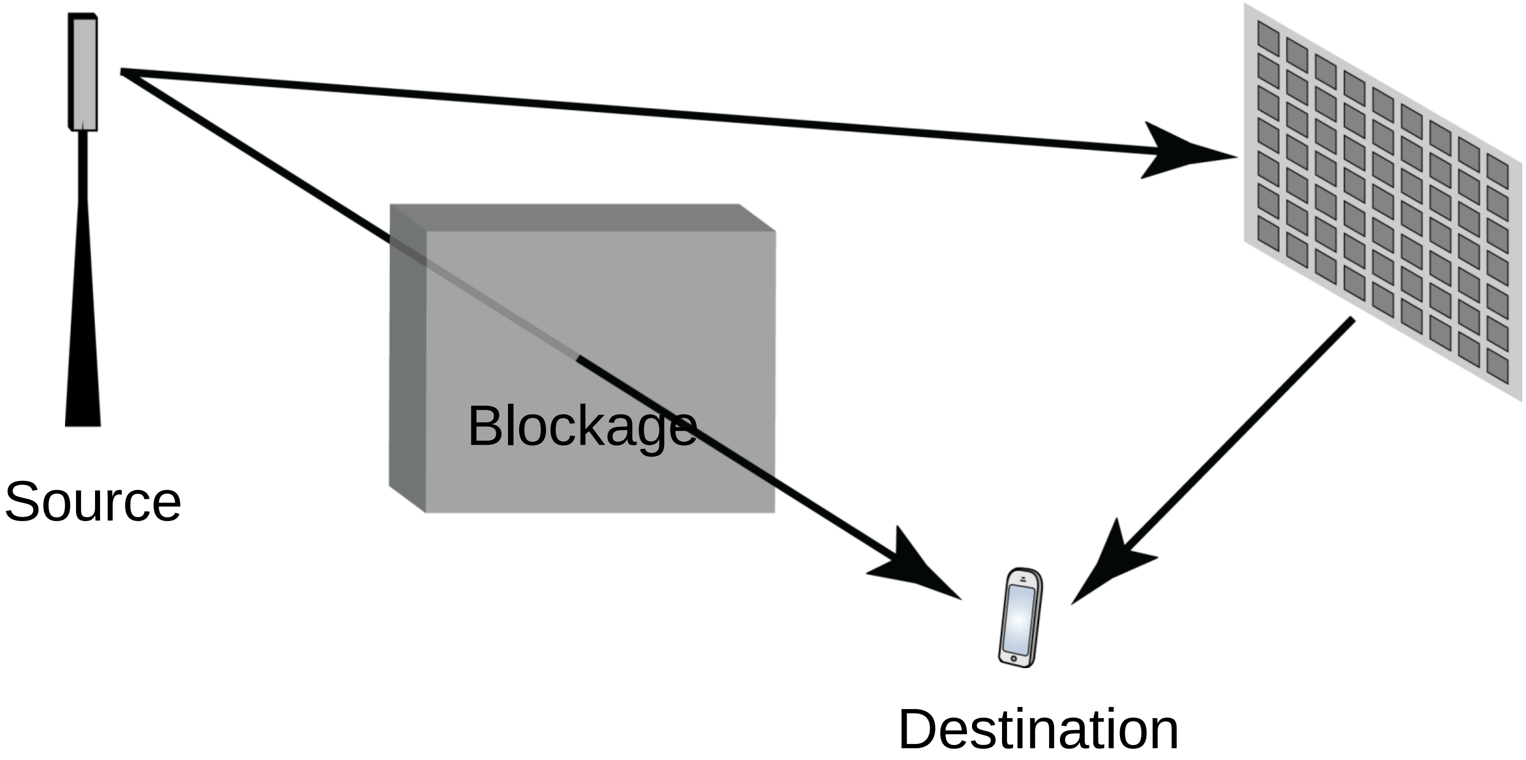
We conventionally control

1) Transmitter
2) Receiver

Now we can control the channel!

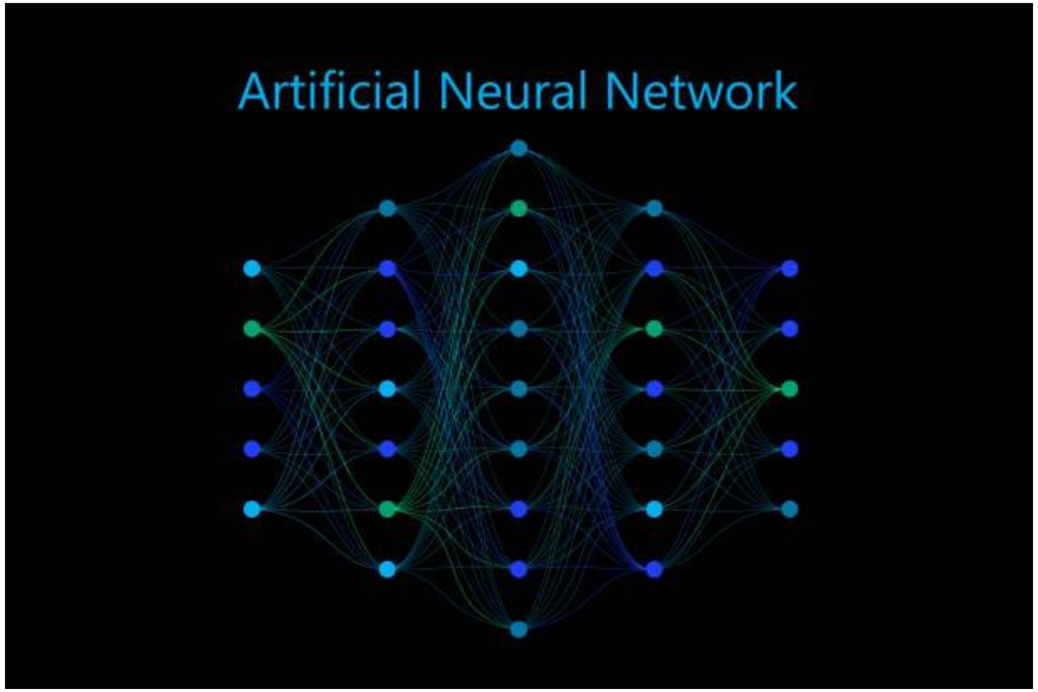
Is this a game changer?

Several myths exist!



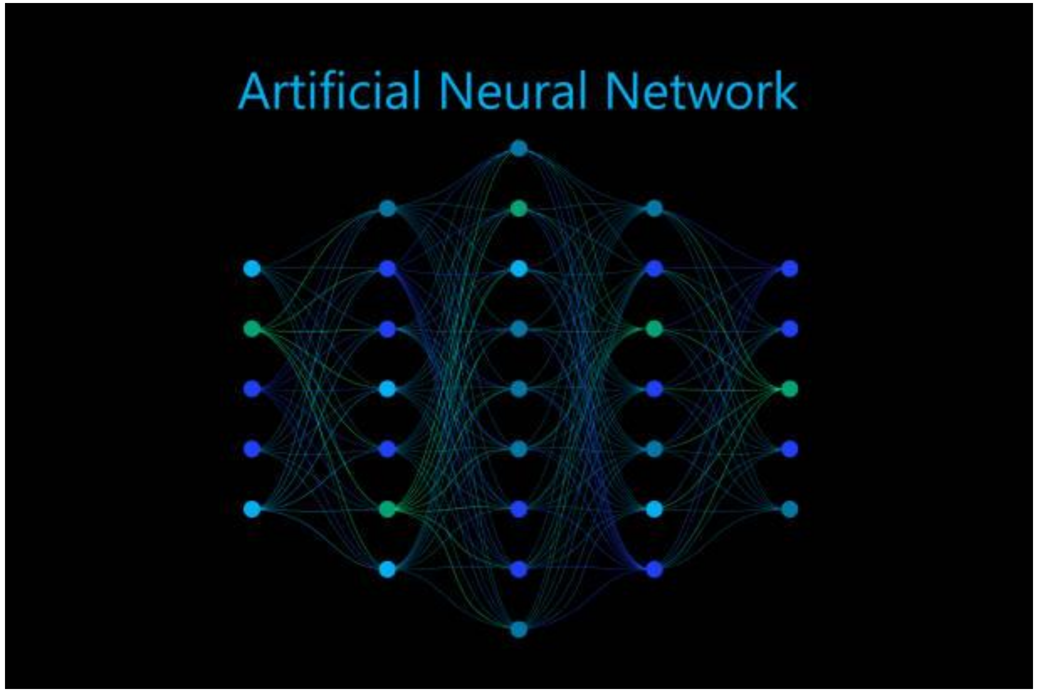
The Role of Deep learning in smart radio environments

- data acquisition and processing
- Tx, Rx and each Reconfigurable Intelligent Surface is variable
- Optimization approach does not work anymore even for offline problem
- Simplifying the resource management leads to energy efficiency



ANNs deployment into wireless networks

- ❖ Cloudily
- ❖ Distributed learning
- ❖ Edge Computing and Federated learning



- ❖ Latency
- ❖ Privacy in vertical application
- ❖ Connectivity
- ❖ individual intelligence alongside collective intelligence

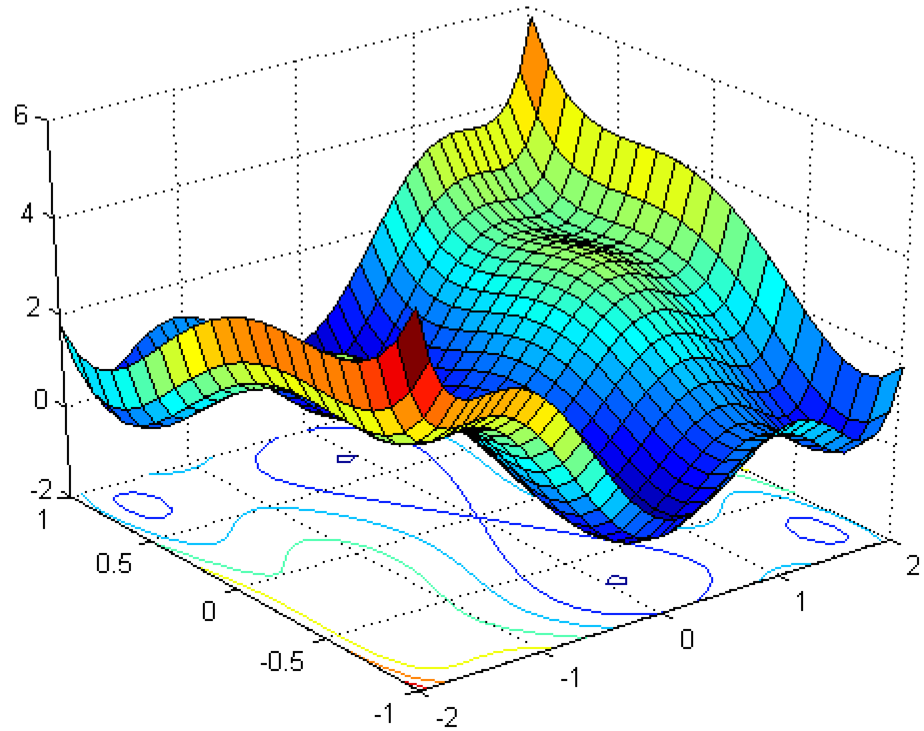
Energy efficiency optimization by deep learning

mathematical formulation

- ❖ function approximations
- ❖ Learning alongside solving
- ❖ Improve

only an approximate model is available

- ❖ Pretraining
- ❖ Transfer Learning
- ❖ Fine Tune



Weighted sum energy efficiency maximization

- uplink of a network with M BSs and K mobile users
- w_k: importance given to the energy efficiency
- $P_{c.k}$: the hardware static power consumption
- μ_k: the inverse of the power amplifier efficiency

$$\gamma_k = \frac{p_k \left|\boldsymbol{c}_k^H \boldsymbol{h}_{k.m_k}\right|^2}{\sigma^2 + \sum_{j \neq k} p_j \left|\boldsymbol{c}_j^H \boldsymbol{h}_{j.m_k}\right|^2} = \frac{p_k d_{k.k}}{\sum_{j \neq k} p_j d_{k.j}} \ ,$$

$$with\ d_{k.j} = \left|\boldsymbol{c}_j^H \boldsymbol{h}_{j.m_k}\right|^2 .\ for\ all\ k.j,$$

$$WSEE = \sum_{k=1}^{K} w_k \frac{B \log_2(1+\gamma_k)}{P_{c.k} + \mu_k p_k} \left(\frac{bit}{J}\right).$$

Weighted sum energy efficiency maximization

- the sum of fractions are non-polynomial-hard
- each numerator of the summands of the
- WSEE is not concave.

$$\max_{\{p_k\}_{k=1}^{K}} \mathrm{WSEE}(p_1. \dots . p_K)$$

$$\text{s.t. } P_{min.k} \leq p_k \leq P_{max.k}. \forall k = 1. \dots . K.$$

Adopting ANN

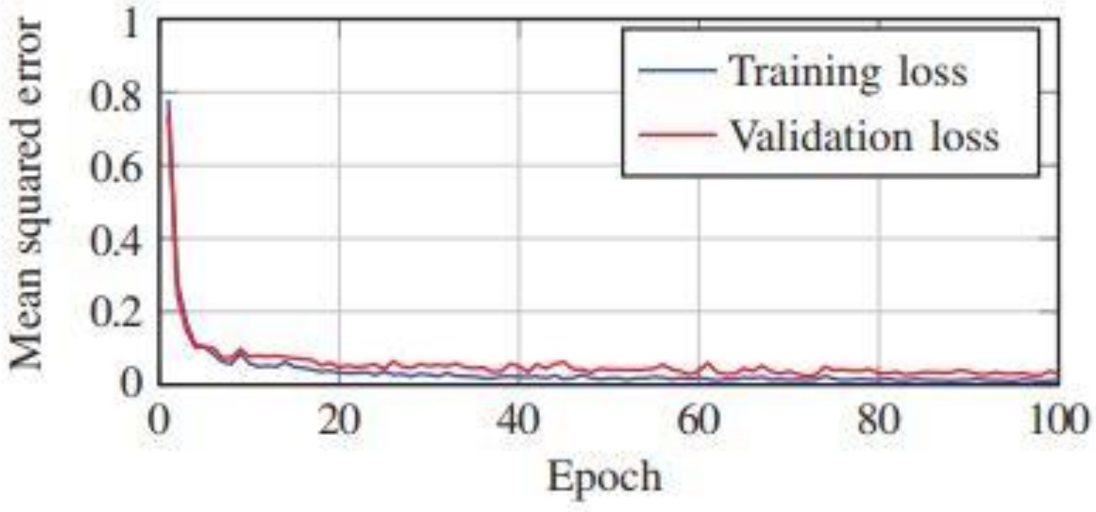
$$\mathcal{F}: \mathbf{d} = \{d_{k.\ell}. P_{min.k}. P_{max.k}\}_{k.\ell} \in \mathbb{R}^{K(M+2)} \rightarrow p^* \in \mathbb{R}^K$$

- Offline Phase: long term training
- Dataset generation & Implementing model

- Online phase: run in coherent time
- ANN must be trained again after coherent time

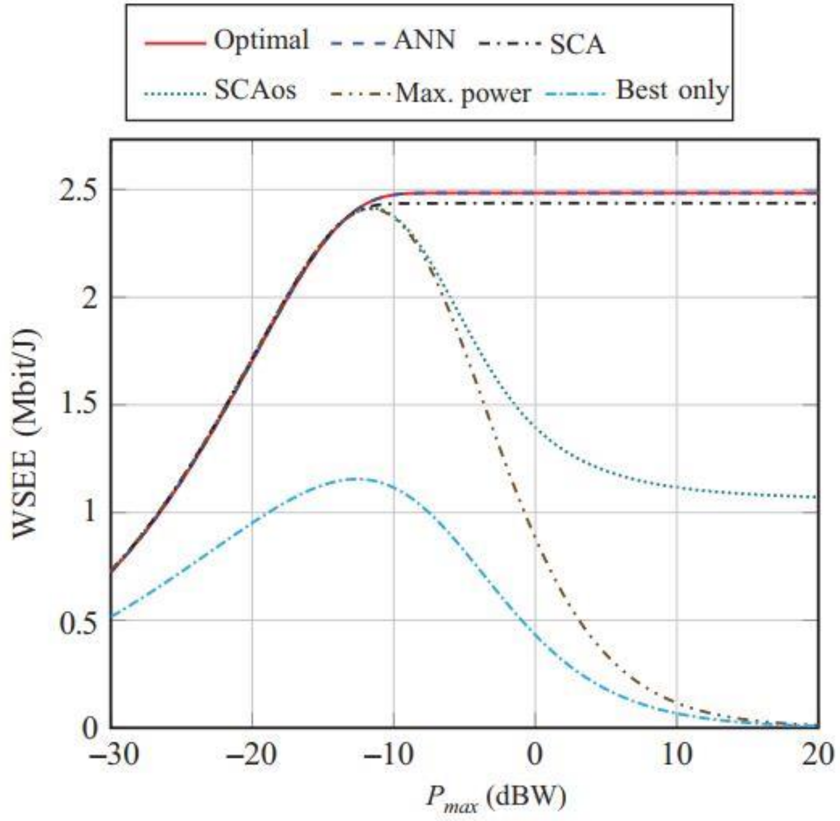
Numerical performance analysis

- Generating iid realization of UE's position & Channel condition for training set
- Generating non-iid data for collaborative learning
- Solving optimization problem takes 4.86e-2 sec, while ANN feed forward takes 4.76e-6 sec.
- Good memorization & generalization in training set & validation set.



Numerical performance analysis

- **SCAos**: sequential convex approximation (SCA) methods
- **SCA**: sequential convex approximation with a double-initialization approach
- **Max. power:** interference networks for low $\boldsymbol{P_{max}}$
- **Best only:** a naive way of nulling out multi-user interference with high $\boldsymbol{P_{max}}$



EE in non-Poisson wireless networks

- EE in non-Poisson density for BSs : intractable optimization problem (utility function)
- Transfer learning & fine tuning
- Suppose wireless network are distributed following a Poisson point process for generating dataset
- Training a ANN and produce pre-train model
- Gathering experimental data from non-poisson process
- Fine tune the pre-train model with experimental data

EE in non-Poisson wireless networks

Poisson point process assumption

- $\boldsymbol{SE}$: spectral efficiency
- $\boldsymbol{P_{grid}}$: power consumption
- $\boldsymbol{\lambda_{BS}}$: deployment density of BSs
- $\boldsymbol{P_{tx}}$: transmit power of the BSs
- **Objective**: $\boldsymbol{\lambda_{BS}}$ given $\boldsymbol{P_{tx}}$

$$\mathrm{EE}(\lambda_{\mathrm{BS}}) = \frac{\mathrm{SE}(\lambda_{\mathrm{BS}})}{P_{\mathrm{grid}}(\lambda_{\mathrm{BS}})}$$

$$\mathrm{SE}(\lambda_{\mathrm{BS}}) = B_{\mathrm{W}} \log_2(1+\gamma_{\mathrm{D}}) \frac{\lambda_{\mathrm{BS}} L\left(\frac{\lambda_{\mathrm{MT}}}{\lambda_{\mathrm{BS}}}\right)}{1+\Upsilon L\left(\frac{\lambda_{\mathrm{MT}}}{\lambda_{\mathrm{BS}}}\right)} \times Q\left(\lambda_{\mathrm{BS}}.P_{\mathrm{tx}}.\frac{\lambda_{\mathrm{MT}}}{\lambda_{\mathrm{BS}}}\right)$$

$$P_{\mathrm{grid}}(\lambda_{\mathrm{BS}}) = \lambda_{\mathrm{BS}} P_{\mathrm{tx}} L\left(\frac{\lambda_{\mathrm{MT}}}{\lambda_{\mathrm{BS}}}\right) + \lambda_{\mathrm{MT}} P_{\mathrm{circ}} + \lambda_{\mathrm{BS}} P_{\mathrm{idle}}\left(1 - L\left(\frac{\lambda_{\mathrm{MT}}}{\lambda_{\mathrm{BS}}}\right)\right)$$

ANN Training

- Input: $\boldsymbol{P_{tx}}$
- Output: $\boldsymbol{\lambda_{BS}}$

optimization problem has a unique solution, which corresponds to the unique root of a non-linear equation

Data-driven optimization: Transfer Learning

$$\mathrm{PSE}(\cdot) = \frac{1}{\text{AreaNet}} \sum_{\text{Cell}(1)\backslash\text{inNet}} \sum_{N_{\mathrm{MT}} \in \text{Cell}(1)} \frac{B_{\mathrm{W}}}{N_{\mathrm{MT}}} \log_2(1+\gamma_{\mathrm{D}}) \mathbf{1}\left(\mathrm{SIR} \geq \gamma_{\mathrm{D}}. \overline{\mathrm{SNR}} \geq \gamma_{\mathrm{A}}\right).$$

$$P_{\text{grid}}\,(.) = \frac{1}{\text{AreaNet}} \left(\sum_{\text{Cell }(0) \in \text{ Net}} P_{\text{idle}} + \sum_{\text{Cell}(1)\backslash\text{inNet}} \left(P_{\text{tx}} + P_{\text{circ}} \sum_{N_{\mathrm{MT}} \in \text{ Cell }(1)} N_{\mathrm{MT}} \right) \right) \cdot$$

If the optimization variable is the BS density, all possible values of density need to be tested, and the value corresponding to the optimal EE needs to be recorded and used to train an ANN.

Numerical results

$$\mathrm{PSE}(\cdot) = \frac{1}{\text{AreaNet}} \sum_{\text{Cell(1)\textbackslash inNet}} \sum_{N_{\mathrm{MT}} \in \text{Cell(1)}} \frac{B_{\mathrm{W}}}{N_{\mathrm{MT}}} \log_2(1+\gamma_{\mathrm{D}}) \mathbf{1}(\mathrm{SIR} \geq \gamma_{\mathrm{D}}. \overline{\mathrm{SNR}} \geq \gamma_{\mathrm{A}}).$$

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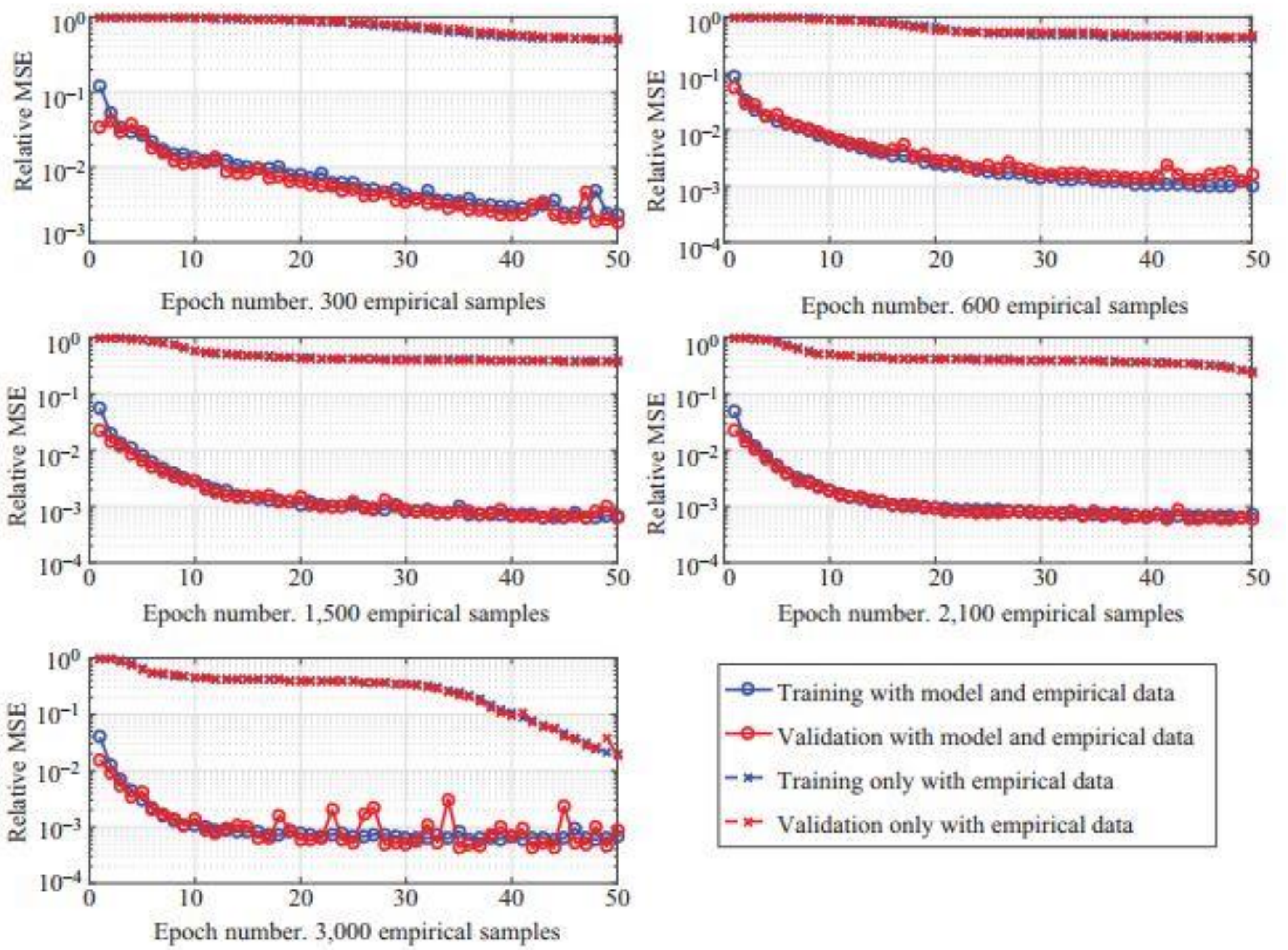

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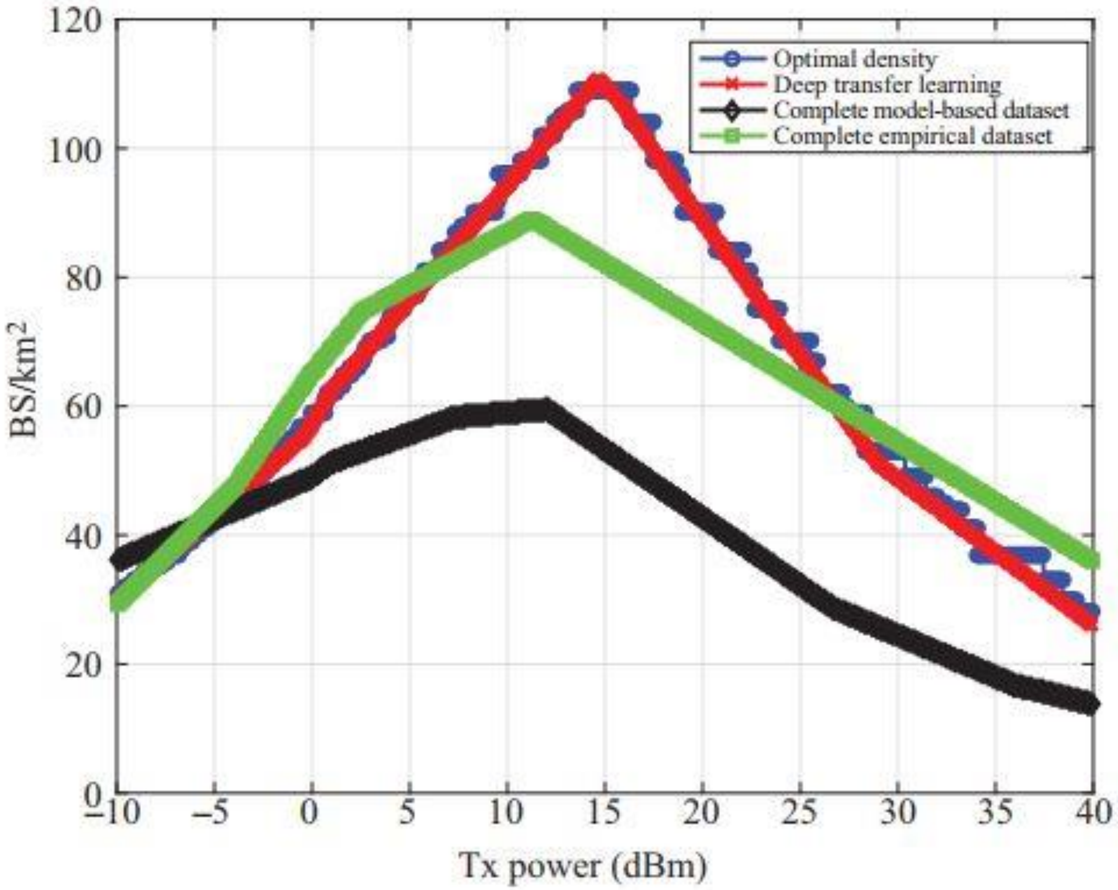

Reference

[1] Suraweera, H. A., Yang, J., Zappone, A., & Thompson, J. S. (2020). Green communications for energy-efficient wireless systems and networks. Institution of Engineering and Technology.