Artificial Intelligence in Electromagnetics and Antennas

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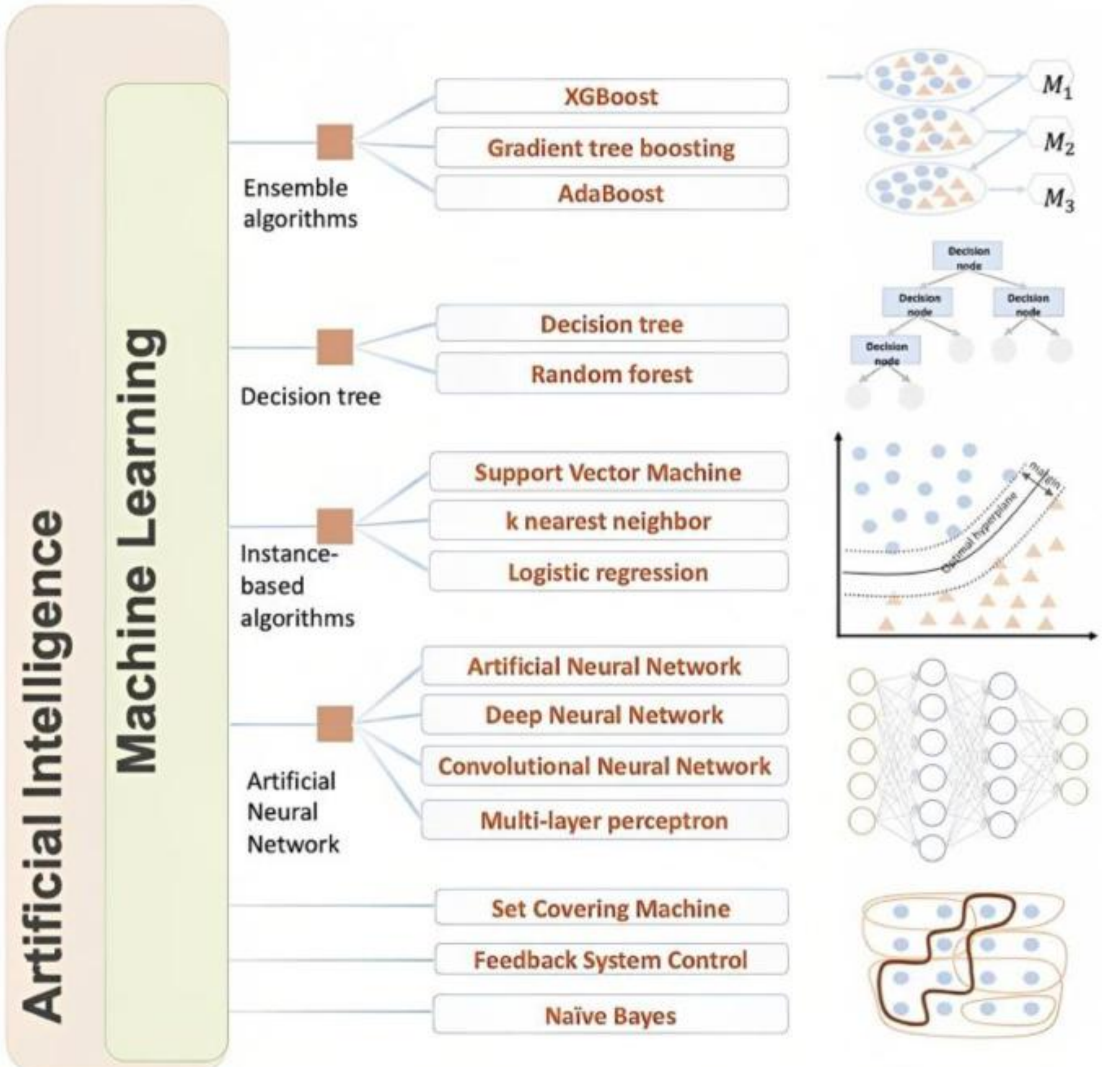
Contents

- Introduction
- Evolutionary algorithms
- Machine Learning in communications
- Inverse problem
- DiffEM4All

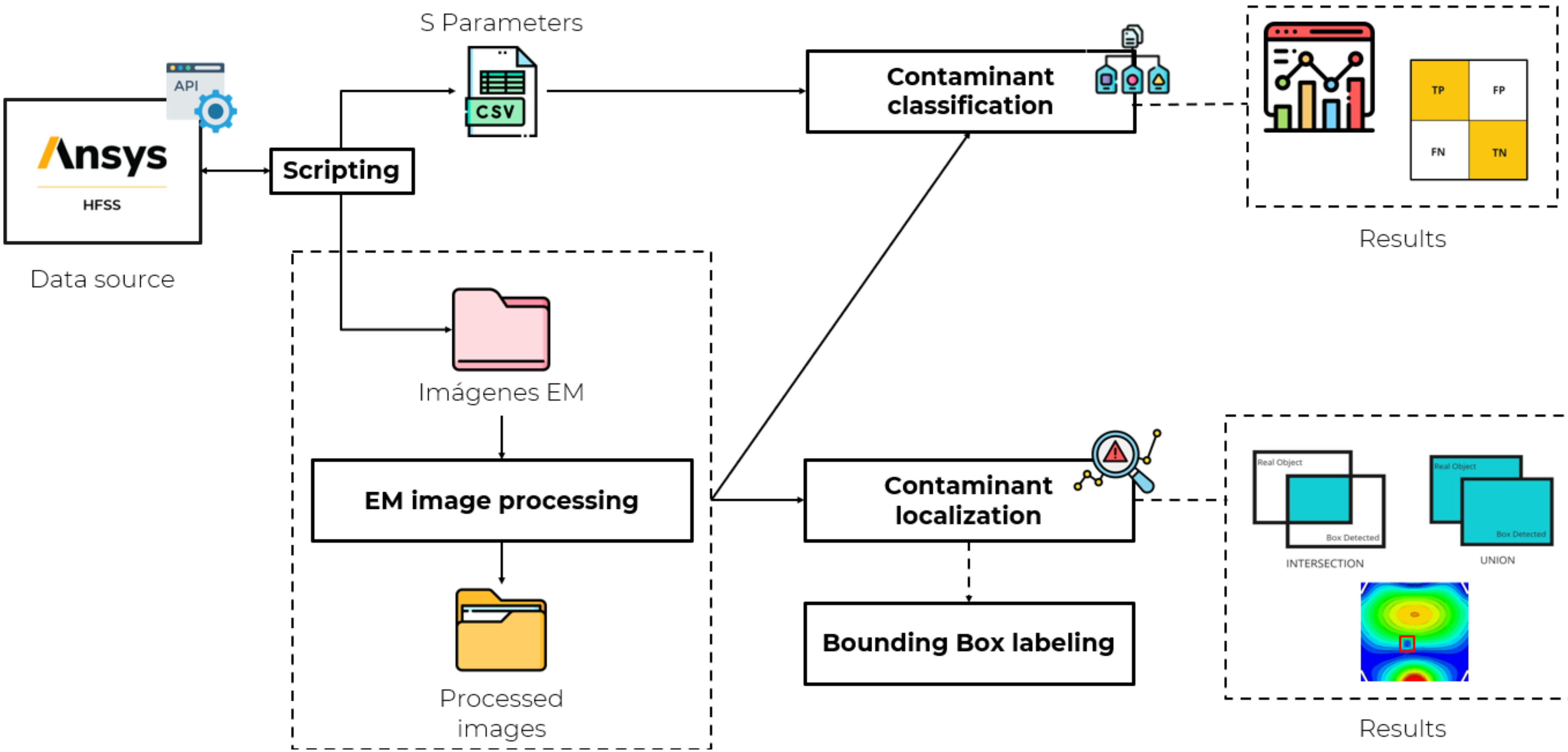
Contents

What is AI?



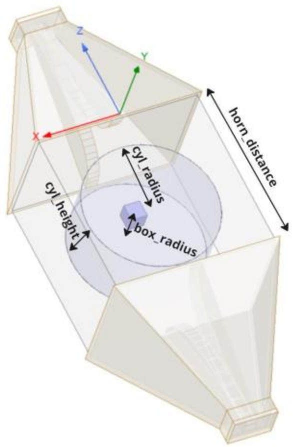
Soori, M., Arezoo, B., & Dastres, R. (2023).
Artificial intelligence, machine learning and deep learning in advanced robotics, a review. *Cognitive Robotics*, *3*, 54–70.
https://doi.org/10.1016/j.cogr.2023.04.001

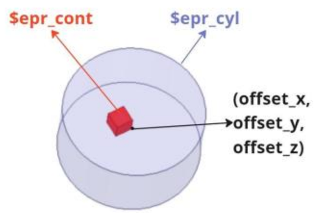
Potential of AI

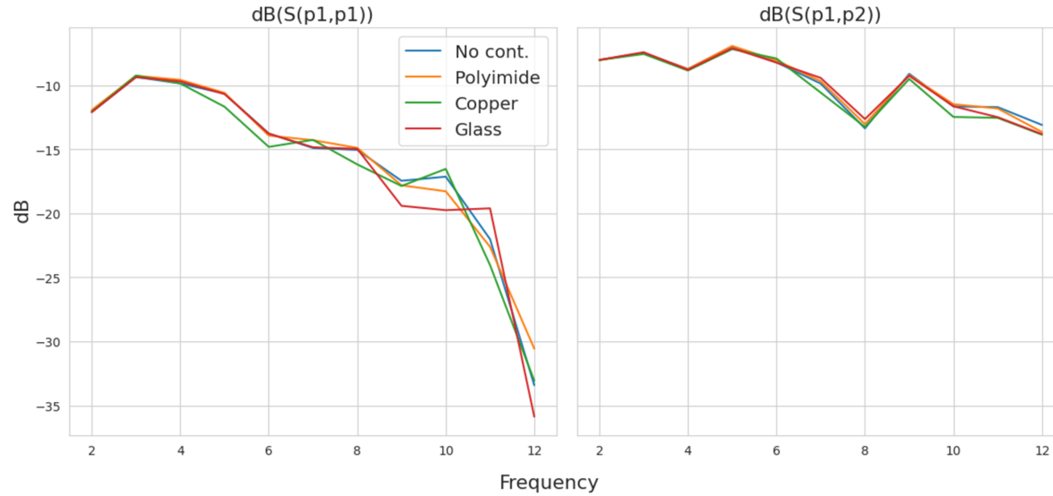


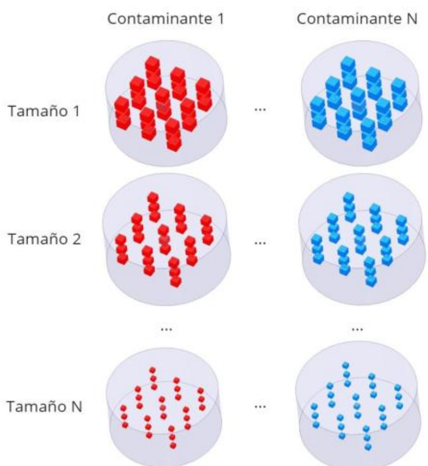
Turienzo-Forcada, C., Amor-Martin, A., & Belloch, J. A. (2023).
Estudio de técnicas de Inteligencia Artificial para la Detección de Contaminantes.
Congreso nacional de la URSI, Cáceres.

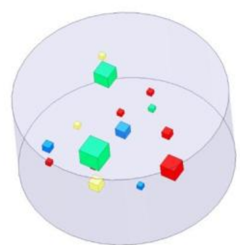
Potential of AI (cont'd)

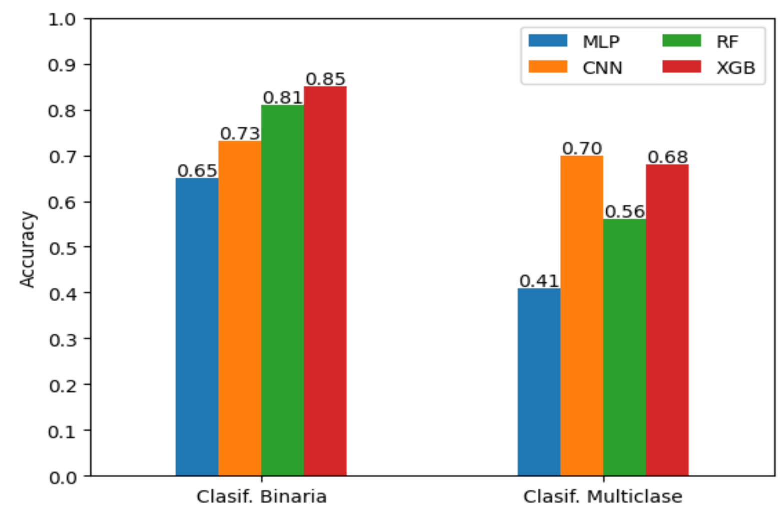












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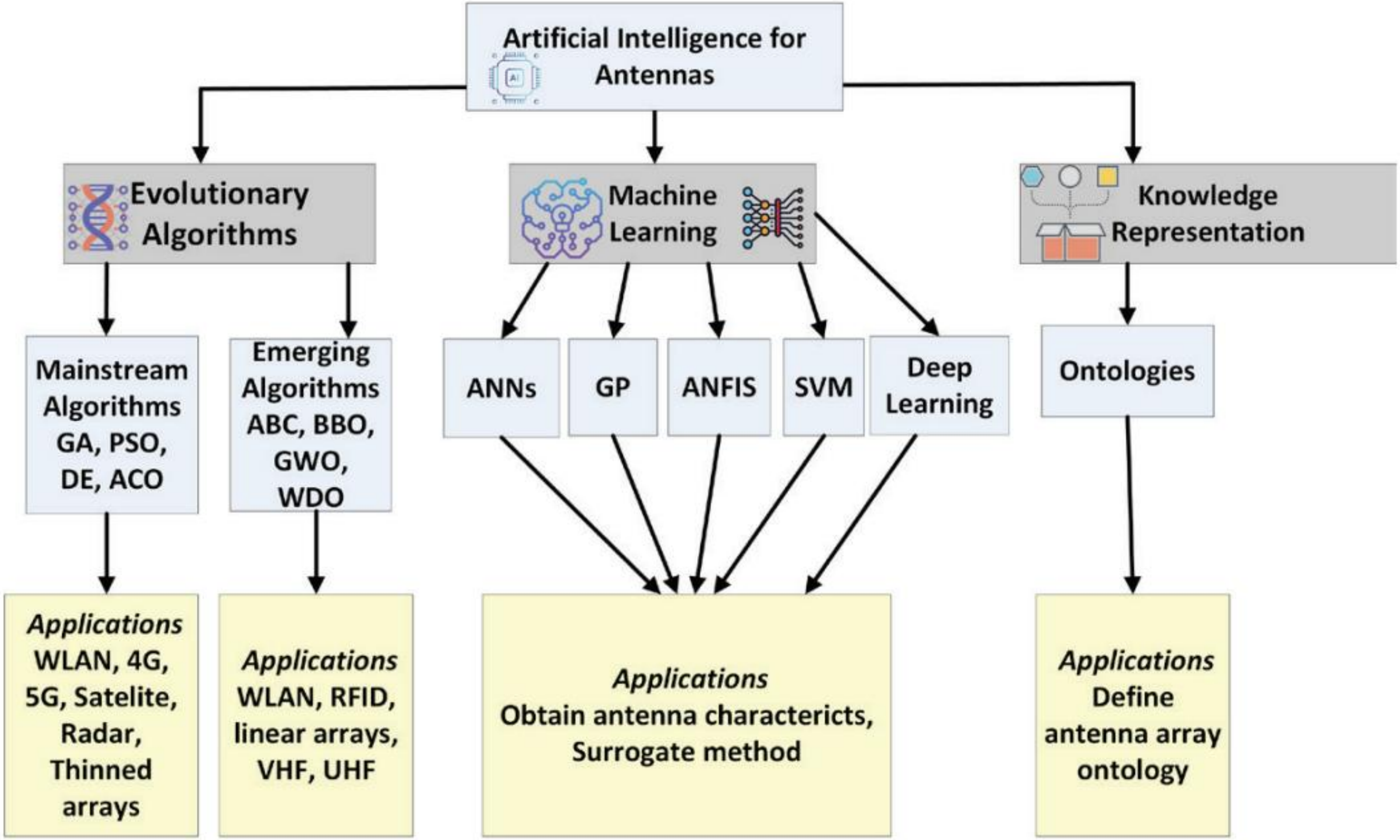
AI for antennas



Goudos, S. K., Diamantoulakis, P. D., Matin, M. A., Sarigiannidis, P., Wan, S., & Karagiannidis, G. K. (2022). Design of antennas through artificial intelligence: State of the art and challenges. *IEEE Communications Magazine*, *60*(12), 96-102.

Interest in the community

- Special issues
  - Haupt, R., & Rocca, P. (2021). Artificial intelligence in electromagnetics [guest editorial]. *IEEE Antennas and Propagation Magazine*, *63*(3), 14-14.
  - Andriulli, F., Chen, P. Y., Erricolo, D., & Jin, J. M. (2022). Guest editorial machine learning in antenna design, modeling, and measurements. *IEEE Transactions on Antennas and Propagation*, *70*(7), 4948-4952.
  - Salucci, M., Arrebola, M., Shan, T., & Li, M. (2022). Artificial intelligence: New frontiers in real-time inverse scattering and electromagnetic imaging. *IEEE Transactions on Antennas and Propagation*, *70*(8), 6349-6364.

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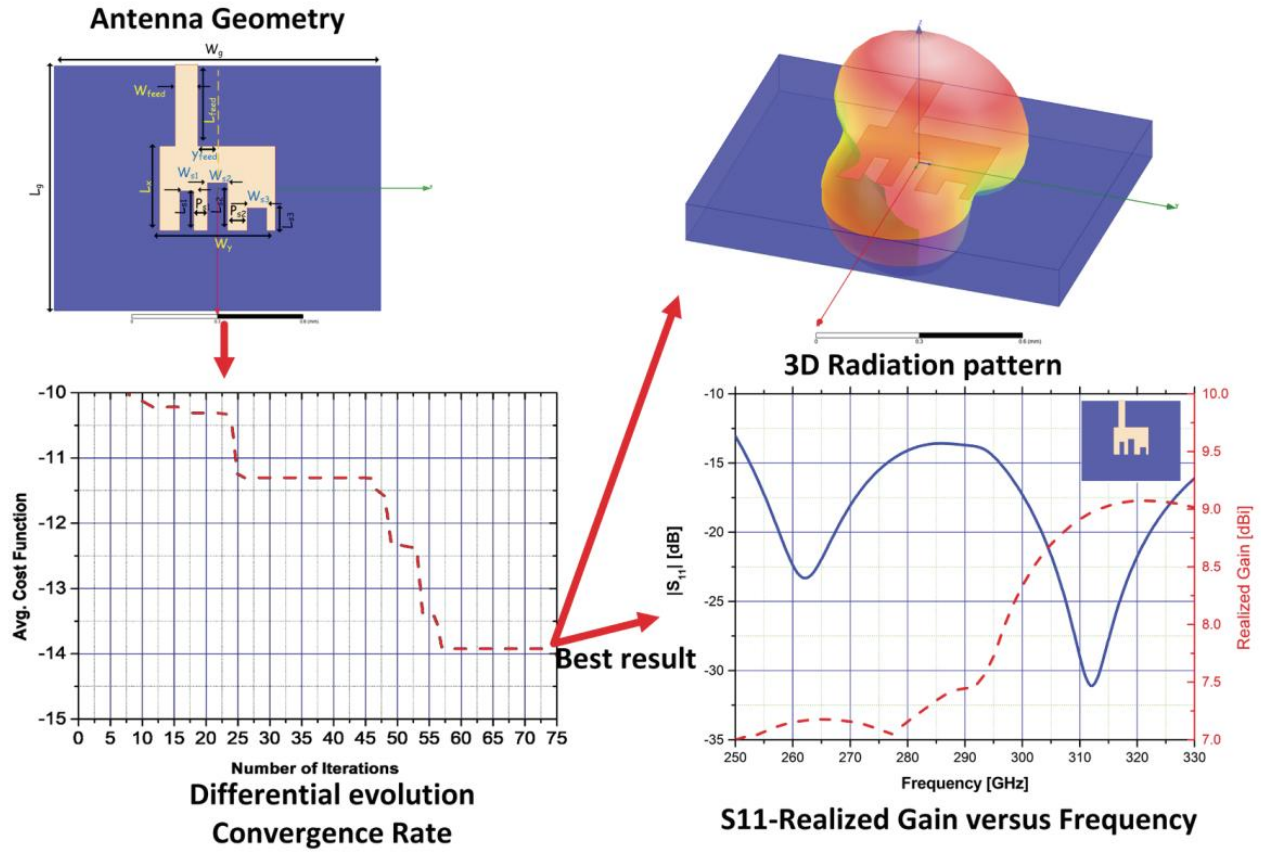
Evolutionary algorithms

- Optimization problems:
  - Optimal geometry for an antenna element
  - Optimization of the locations and excitations of an antenna array
- Genetic algorithms
  - Operators
    - Cross-over: recombines two or more parents to create a new child
    - Mutation: probabilistically alters the current solution
    - Selection: manner in which the parent vectors or chromosomes are recombined.
  - Elitism: the betters solutions survive.
- Particle Swarm Optimization
  - Inspired by how birds' swarms search for food
  - Cognitive learning factor, social learning factor, inertia weight
  - Low-complexity algorithm

Evolutionary algorithms



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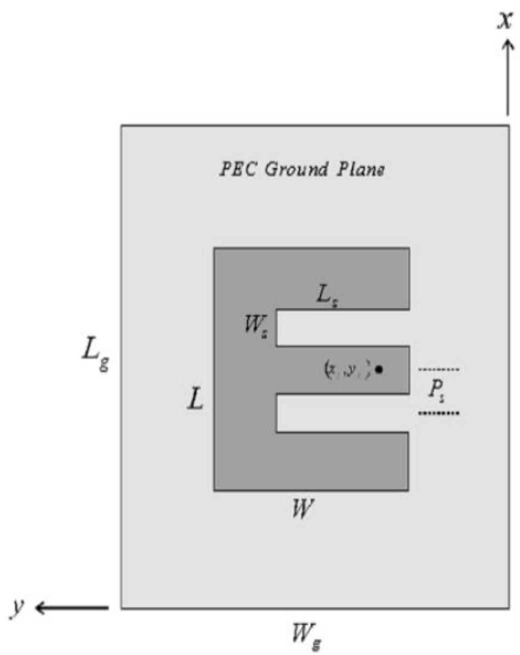
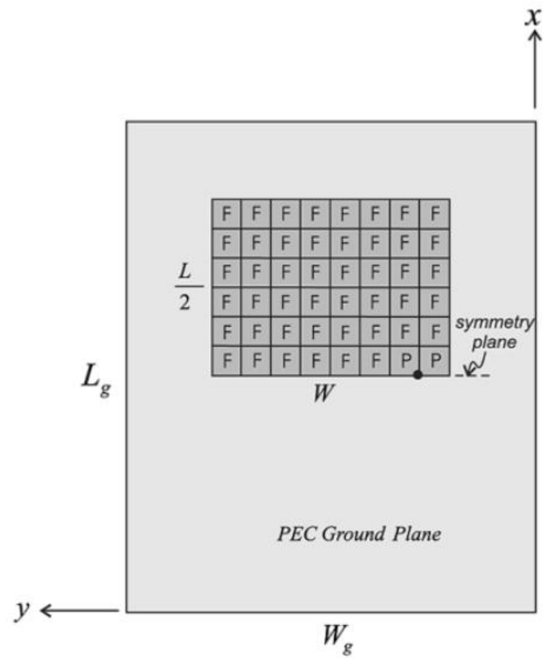
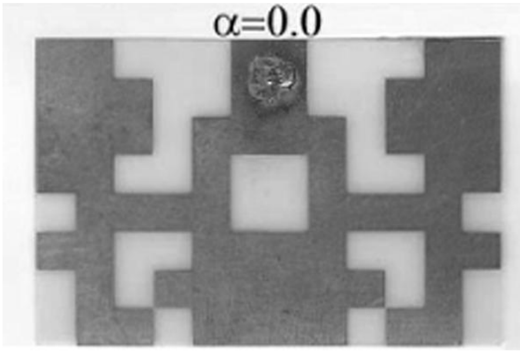
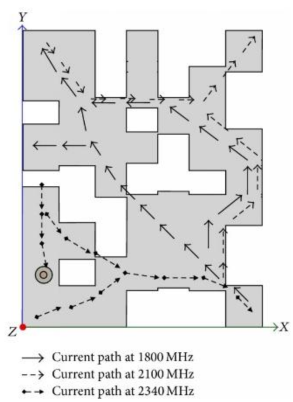
Genetic algorithms

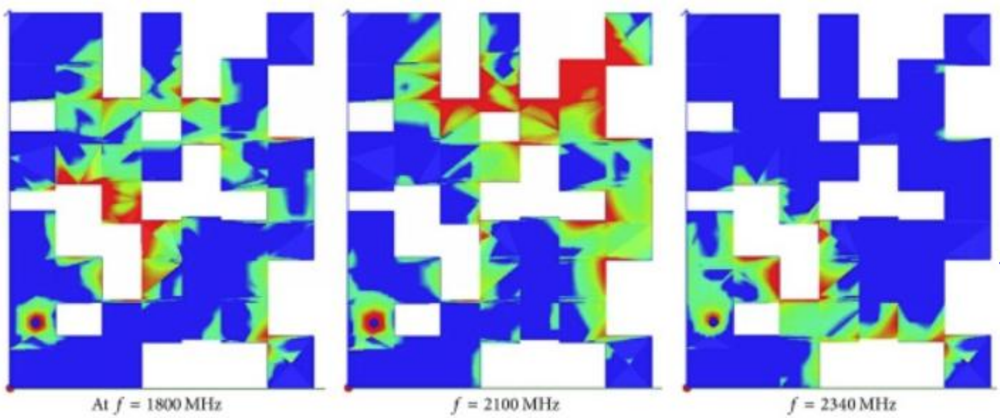




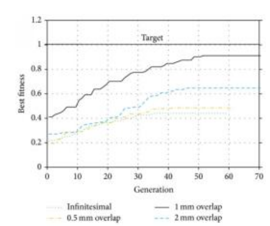


Villegas, F. J., Cwik, T., Rahmat-Samii, Y., & Manteghi, M. (2004).
A parallel electromagnetic genetic-algorithm optimization (EGO) application for patch antenna design.
IEEE Transactions on Antennas and Propagation, *52*(9), 2424-2435.

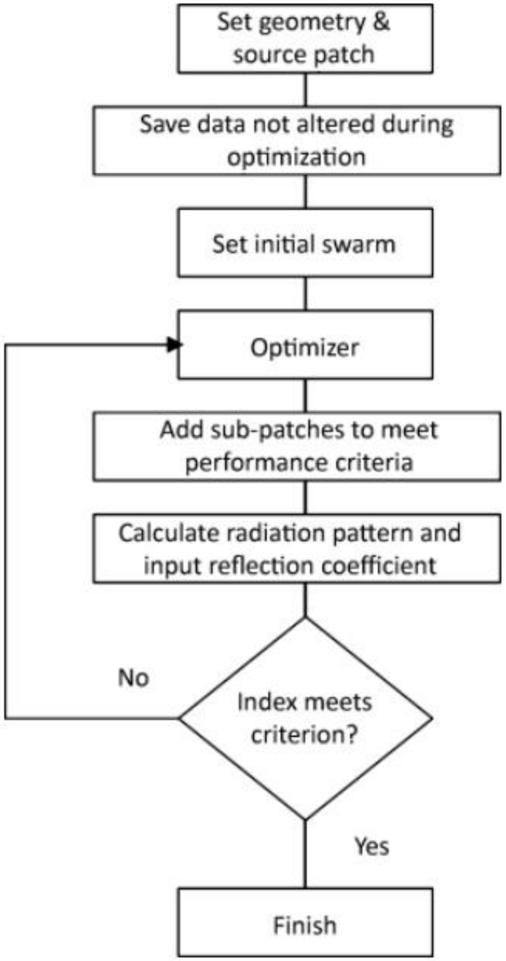


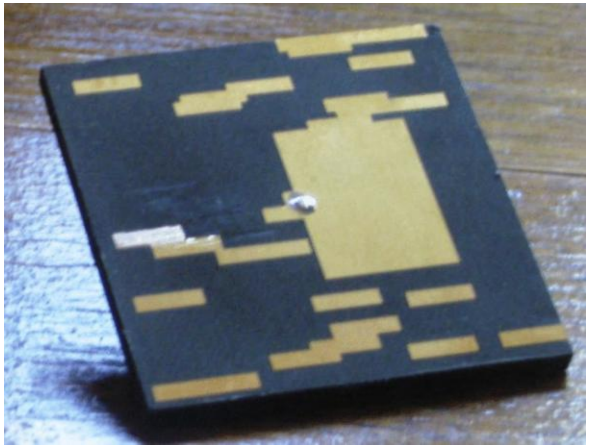


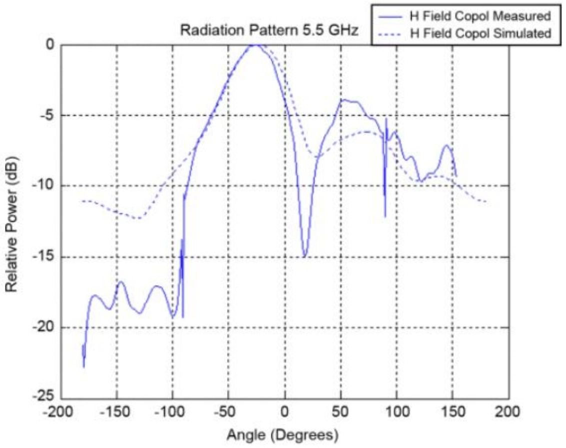
Jayasinghe, J. M. J. W., Anguera, J., Uduwawala, D. N., & Andújar, A. (2015). Nonuniform Overlapping Method in Designing Microstrip Patch Antennas Using Genetic Algorithm Optimization. *International Journal of Antennas and Propagation*, *2015*(1), 805820. https://doi.org/10.1155/2015/805820

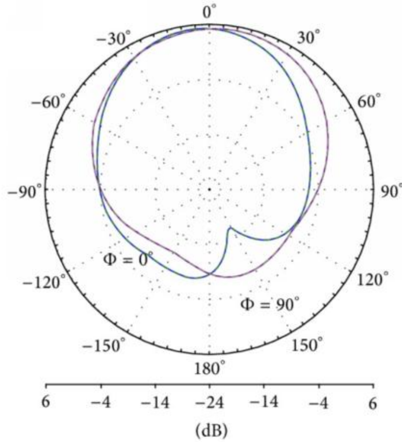


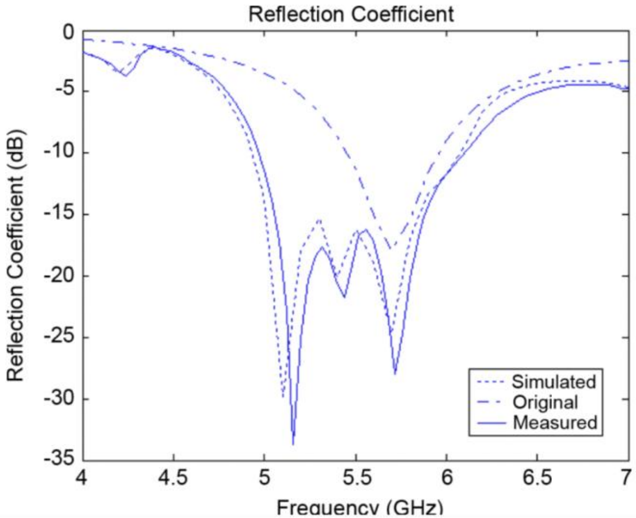
Particle Swarm Optimization





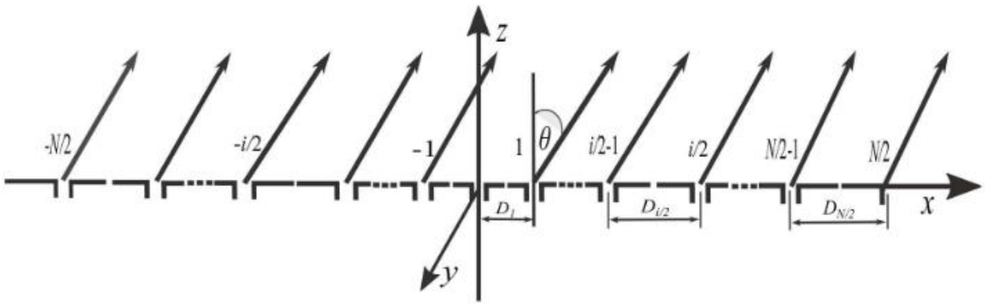






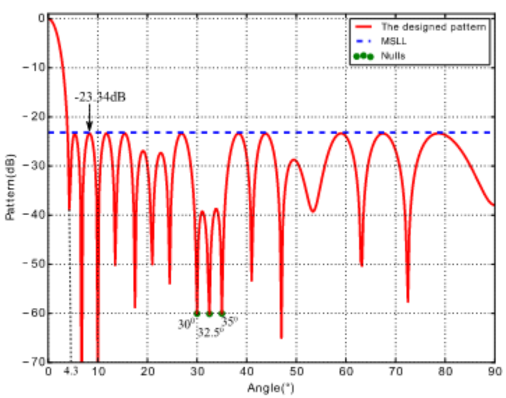
Jayasinghe, J. M. J. W., Anguera, J., Uduwawala, D. N., & Andújar, A. (2015). Nonuniform Overlapping Method in Designing Microstrip Patch Antennas Using Genetic Algorithm Optimization. *International Journal of Antennas and Propagation*, *2015*(1), 805820. https://doi.org/10.1155/2015/805820

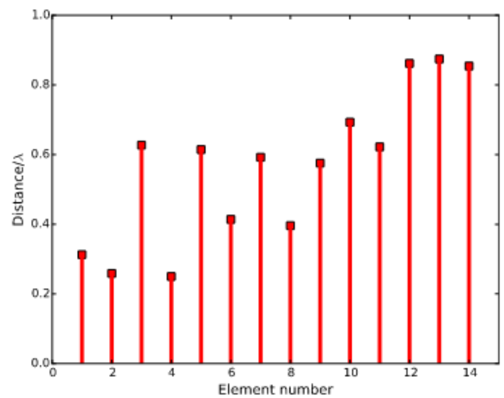
Design of antenna arrays

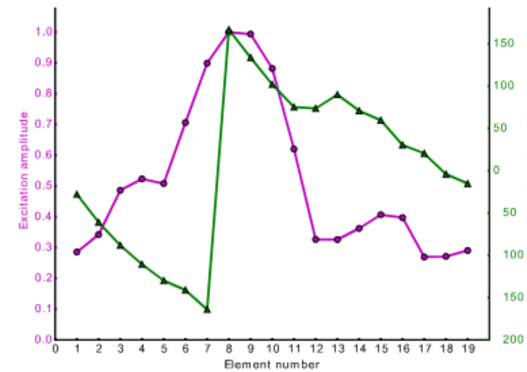


$$\min \ y = f(\vec{x})$$
$$\text{where } \vec{x} = (x_1, x_2, \ldots, x_n) \in \mathbf{X}$$
$$\mathbf{X} = \{\vec{x} | \vec{l} \leq \vec{x} \leq \vec{u}\}$$
$$\vec{l} = (l_1, l_2, \ldots, l_n), \vec{u} = (u_1, u_2, \ldots, u_n)$$

$$\min \ y = f(\vec{x})$$
$$\text{st } \vec{g}(\vec{x}) = (g_1(\vec{x}), g_2(\vec{x}), \ldots, g_p(\vec{x})) \leq \vec{0}$$
$$\text{where } \vec{x} = (x_1, x_2, \ldots, x_n) \in \mathbf{X}$$
$$\mathbf{X} = \{\vec{x} | \vec{l} \leq \vec{x} \leq \vec{u}\}$$
$$\vec{l} = (l_1, l_2, \ldots, l_n), \quad \vec{u} = (u_1, u_2, \ldots, u_n)$$







$$\min \ \vec{y} = \vec{f}(\vec{x}) = (f_1(\vec{x}), f_2(\vec{x}), \ldots, f_m(\vec{x}))$$
$$\text{st } \vec{g}(\vec{x}) = (g_1(\vec{x}), g_2(\vec{x}), \ldots, g_p(\vec{x})) \leq \vec{0}$$
$$\text{where } \vec{x} = (x_1, x_2, \ldots, x_n) \in \mathbf{X}$$
$$\mathbf{X} = \{\vec{x} | \vec{l} \leq \vec{x} \leq \vec{u}\}$$
$$\vec{l} = (l_1, l_2, \ldots, l_n), \quad \vec{u} = (u_1, u_2, \ldots, u_n).$$

Xu, Q., Zeng, S., Zhao, F., Jiao, R., & Li, C. (2021).
On Formulating and Designing Antenna Arrays by Evolutionary Algorithms.
IEEE Transactions on Antennas and Propagation, *69*(2), 1118–1129.
https://doi.org/10.1109/TAP.2020.3016181
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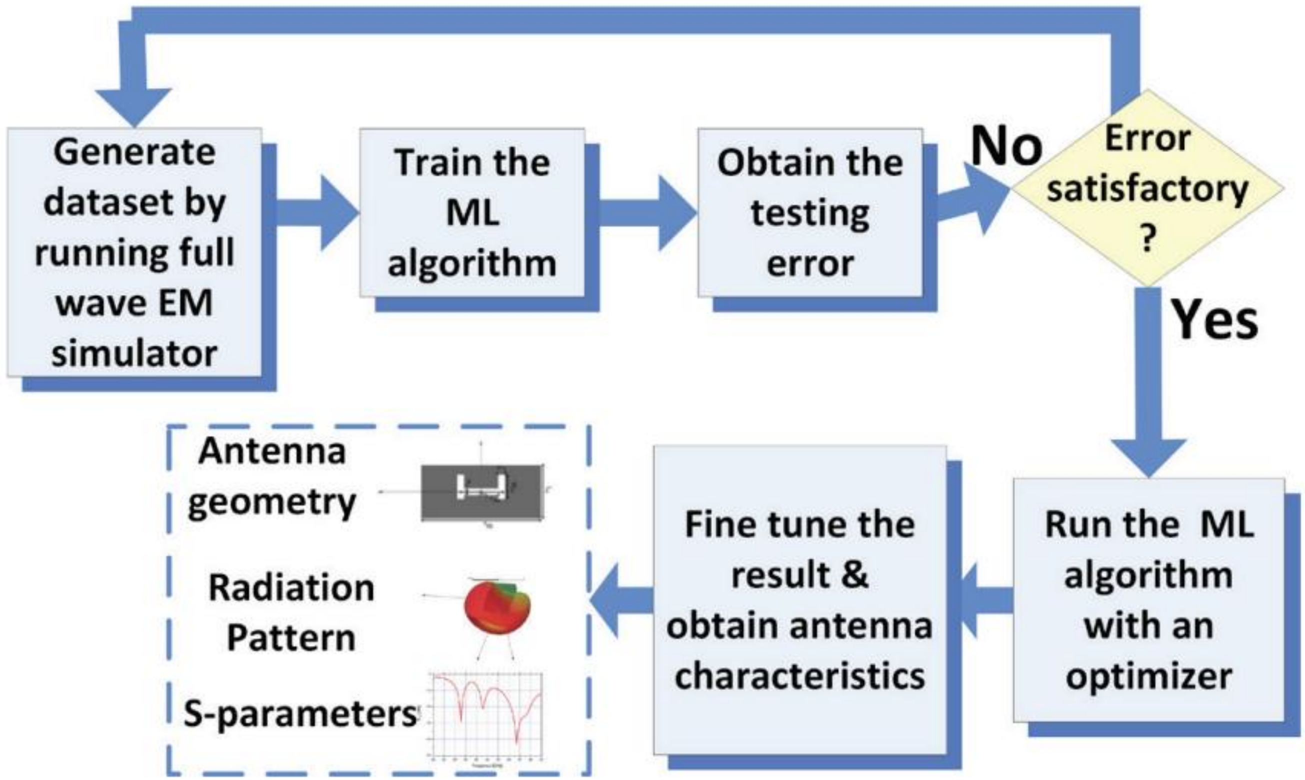
Contents

Machine Learning

- Learn from data
- Antenna design can be seen as a supervised regression task
  - Antenna synthesis
  - Antenna analysis



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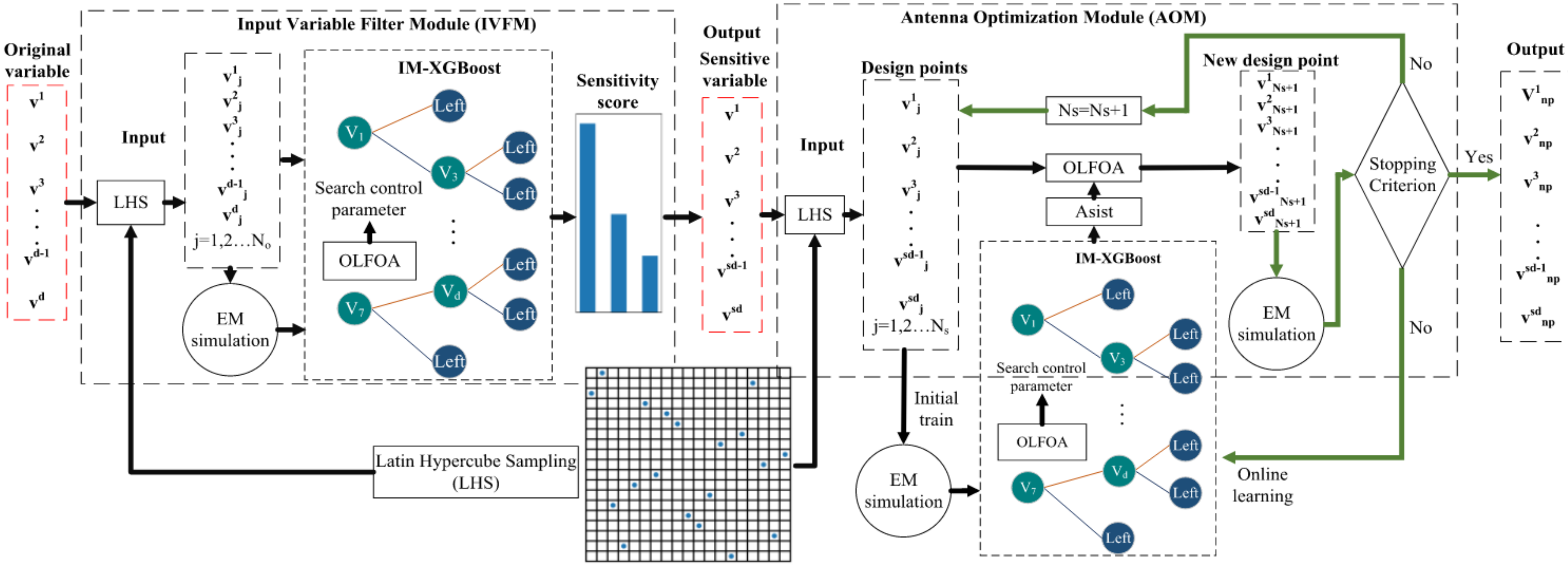
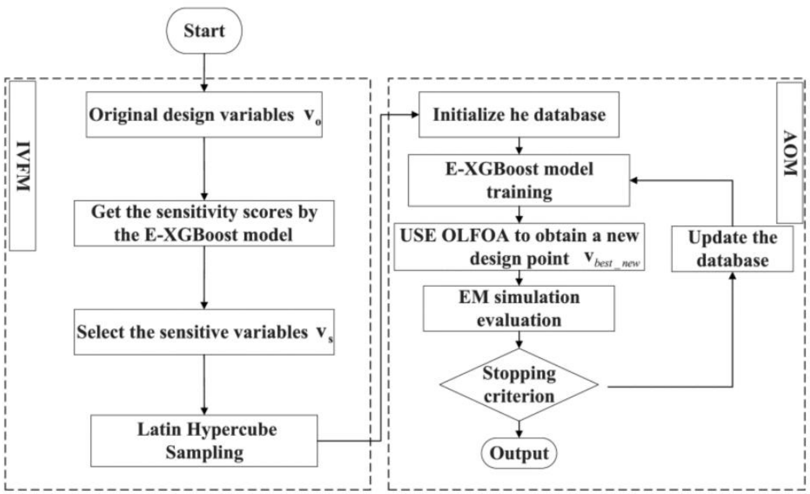
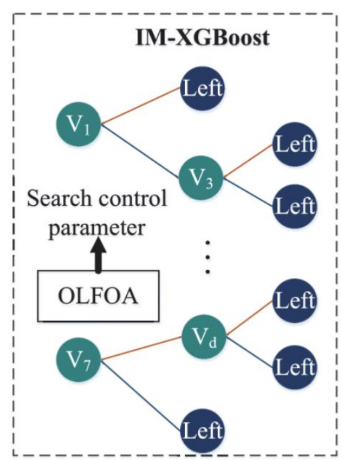
ML in antenna design

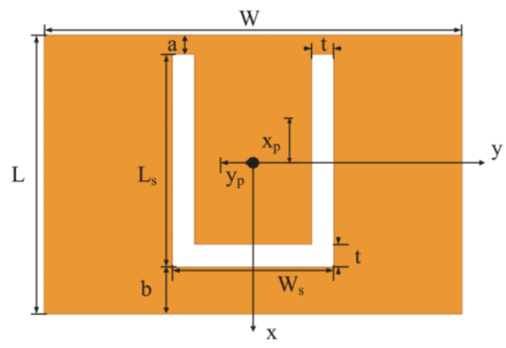




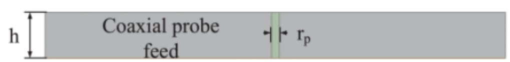


Li, W. T., Tang, H. S., Cui, C., Hei, Y. Q., & Shi, X. W. (2022).
Efficient Online Data-Driven Enhanced-XGBoost Method for Antenna Optimization.
IEEE Transactions on Antennas and Propagation, *70*(7), 4953–4964.
https://doi.org/10.1109/TAP.2022.3157895

ML in antenna design (cont'd)



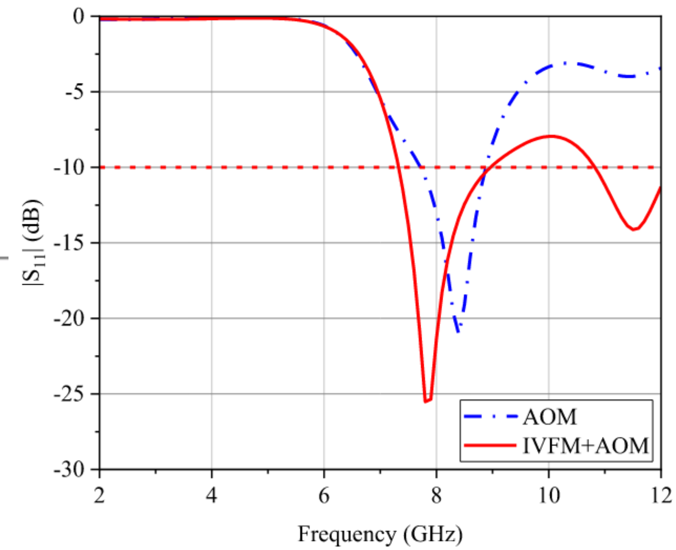
(a)

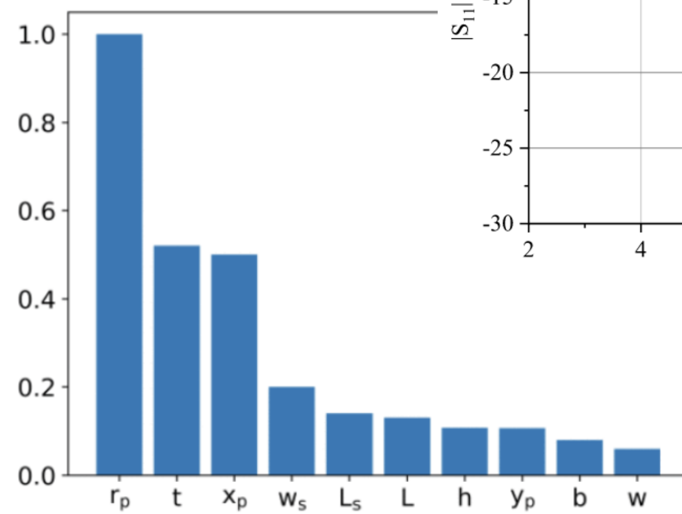


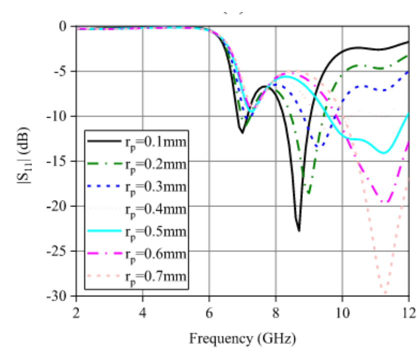
(b)

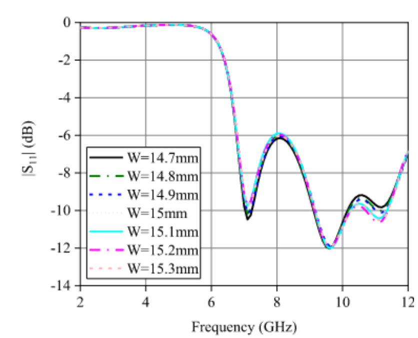
Geometrical variables	MIN	Max
t (mm)	0.5	1.1
L (mm)	9.8	10.4
W (mm)	0.9	1.9
L_s (mm)	7.3	7.9
b (mm)	1.25	1.85
W_s (mm)	5.3	5.9
y_p (mm)	-0.3	0.3
x_p (mm)	-0.3	0.3
r_p (mm)	0.1	0.6
h (mm)	3.0	3.6

M. Khan and D. Chatterjee, Characteristic mode analysis of a class of empirical design techniques for probe-fed, U-slot microstrip patch antennas, *IEEE Trans. Antennas Propag.*, vol. 64, no. 7, pp. 2758–2770, Jul. 2016.









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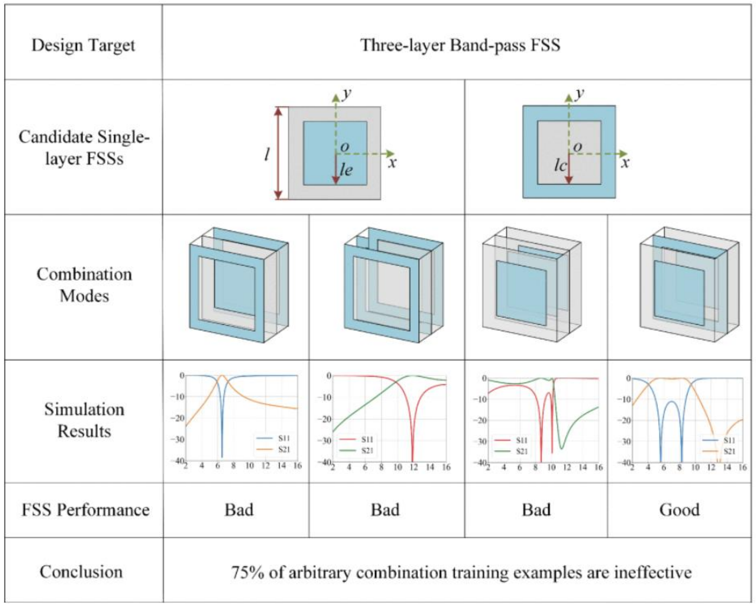
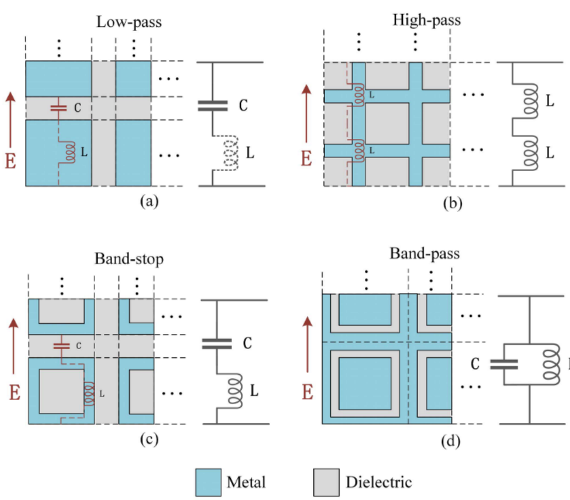
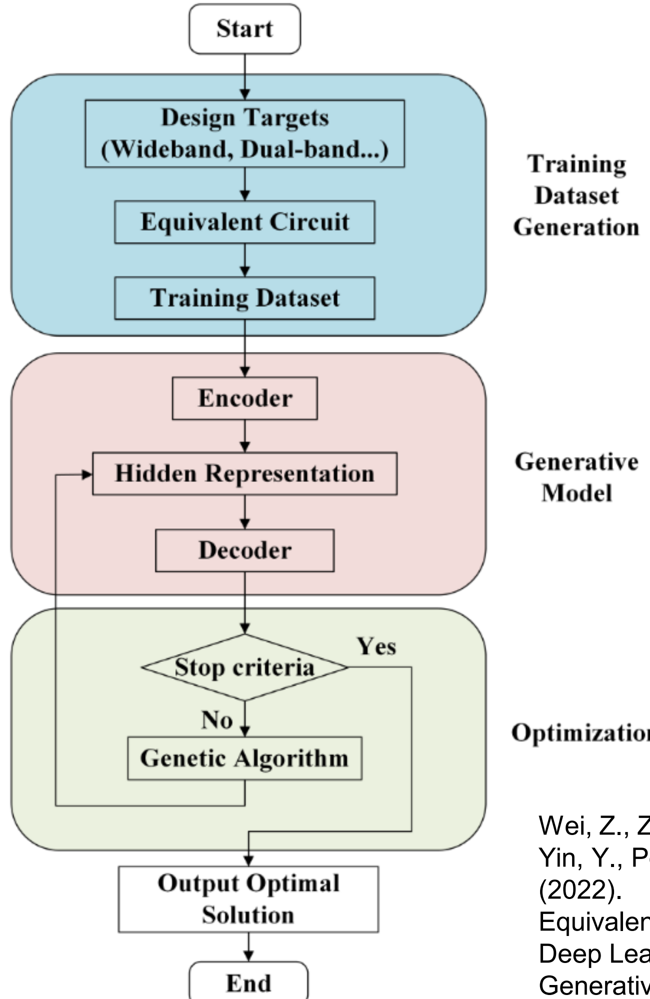
ML for metasurfaces







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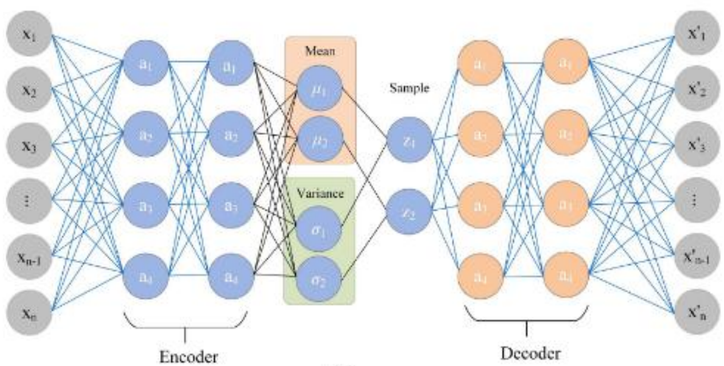
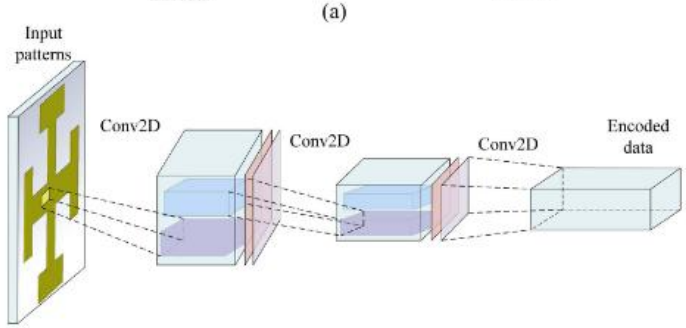
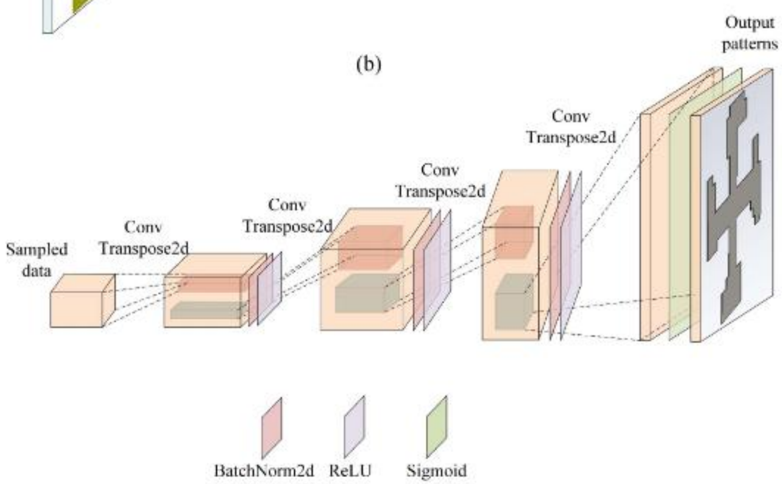
ML for metasurfaces (cont'd)



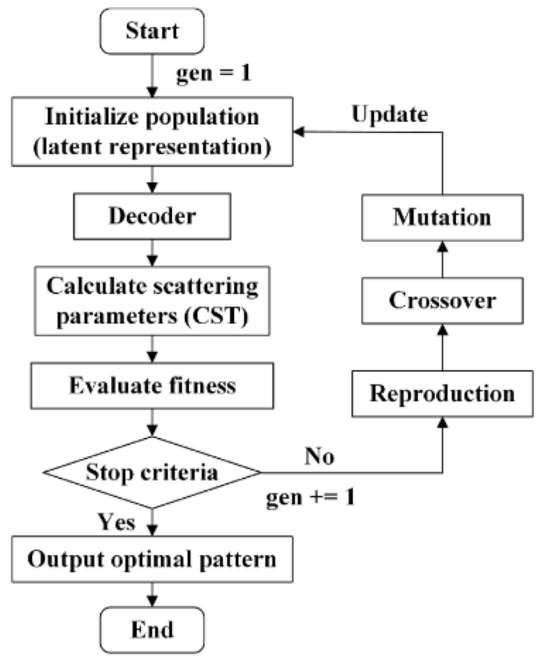
(a)

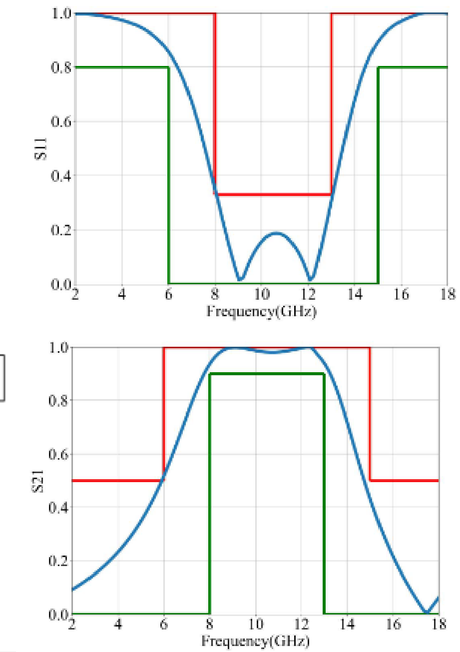


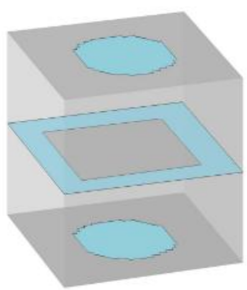
(b)



(c)



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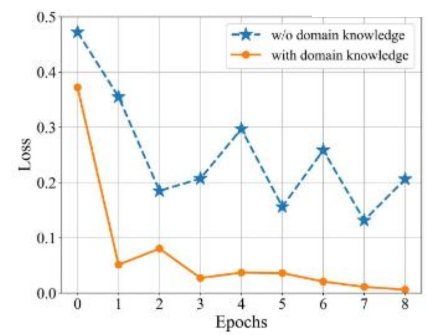

(b)

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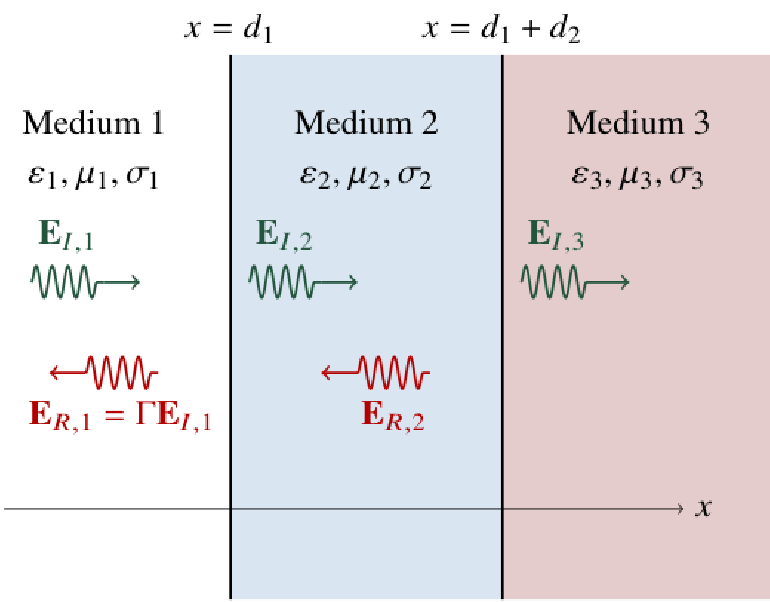
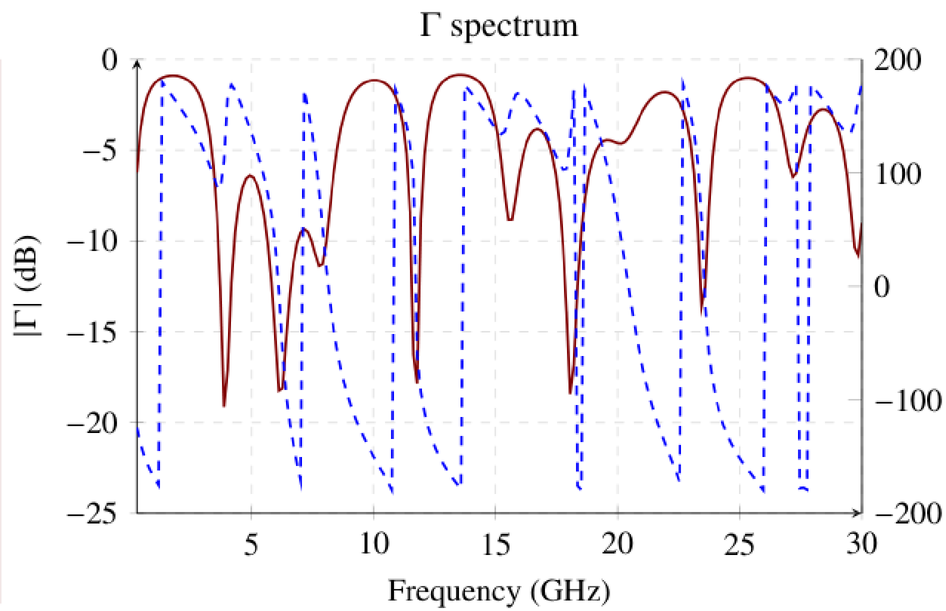
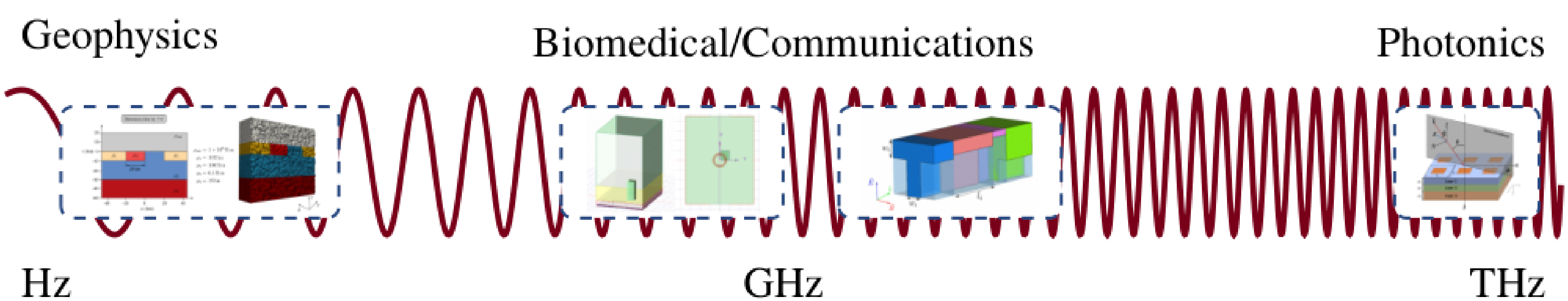
Back to basics

(a) Example of a multilayer problem



(b) Example of $\Gamma(\omega)$ for a multilayer problem

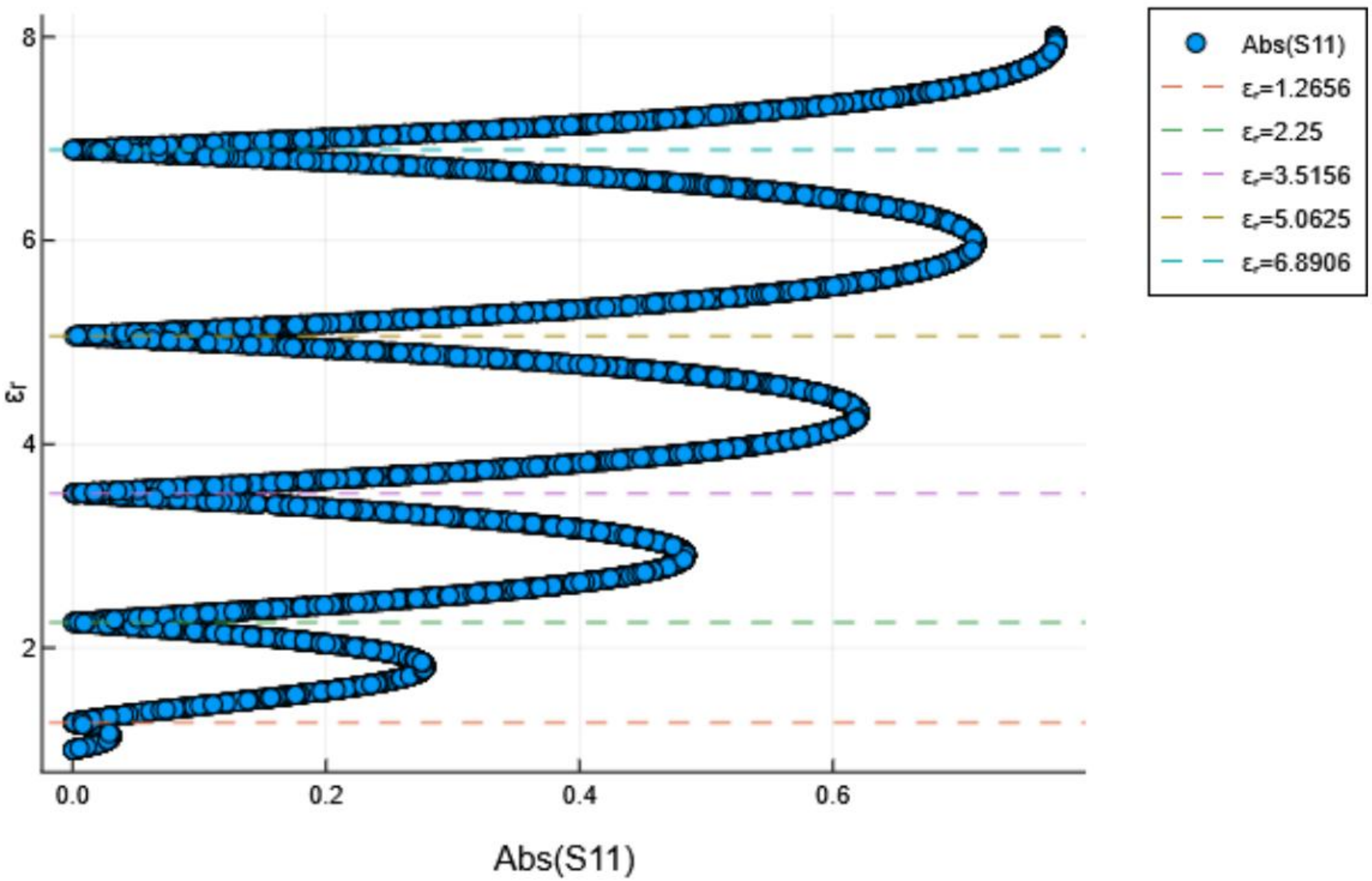




Basic test with AI as black-box model

- Slab with a finite thickness of a given lossless material
  - BW: [1-2] GHz with a resolution of 1000 points
  - $\varepsilon_r \in [5.01 - 60]$
  - Thickness of $d \in [0.01 - 0.1]$
  - Lossless: $\tan\delta = 0$
  - Training only with $|\rho|$.
  - Loss function: smoothL1Loss.
- Three datasets varying the stepsize in $\boldsymbol{\varepsilon_r = [0.1, 0.01, 0.001]}$
  - First dataset: $550 \times 23 \times 1000 \rightarrow 98.71$ MB
  - Second dataset: $5500 \times 23 \times 1000 \rightarrow 986.19$ MB
  - Third dataset: $55000 \times 23 \times 1000 \rightarrow 9859.47$ MB
- Computational details in logs

Ill-conditioned problem



Gómez González, E. (2025).
Inverse Problems in Electromagnetics Using Autodifferentiable Solvers in Julia
Master's Thesis, Master in Multimedia and Communications, Universidad Carlos III de Madrid.

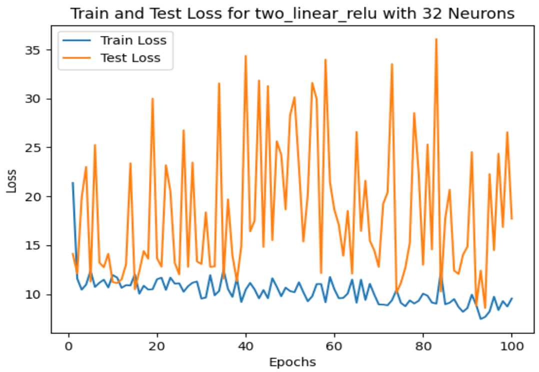
Basic test with AI as black-box model

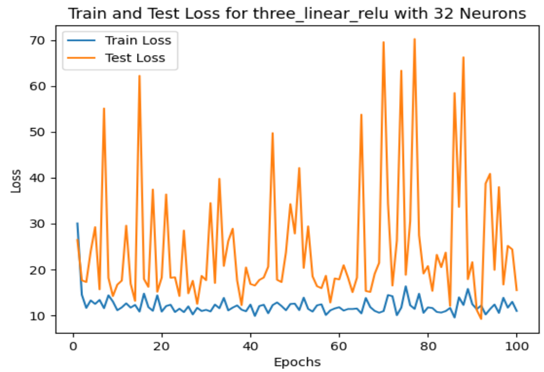
```python
model = nn.Sequential(
            nn.Linear(in_features=IN_FEATURES, out_features=num_hidden_neurons),
            nn.ReLU(),
            nn.Linear(in_features=num_hidden_neurons, out_features=num_hidden_neurons),
            nn.ReLU(),
            nn.Linear(in_features=num_hidden_neurons, out_features=OUT_FEATURES)
).to(device)
```

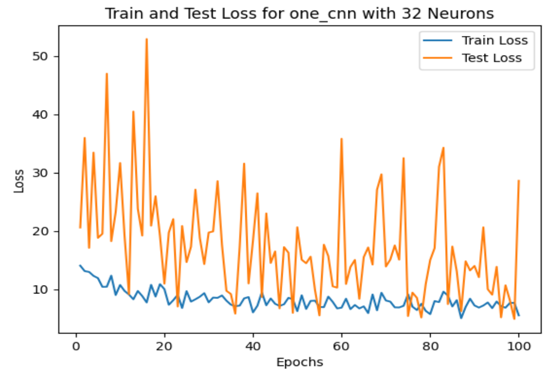
```python
model = nn.Sequential(
            nn.Linear(in_features=IN_FEATURES, out_features=num_hidden_neurons),
            nn.ReLU(),
            nn.Linear(in_features=num_hidden_neurons, out_features=OUT_FEATURES),
).to(device)
```

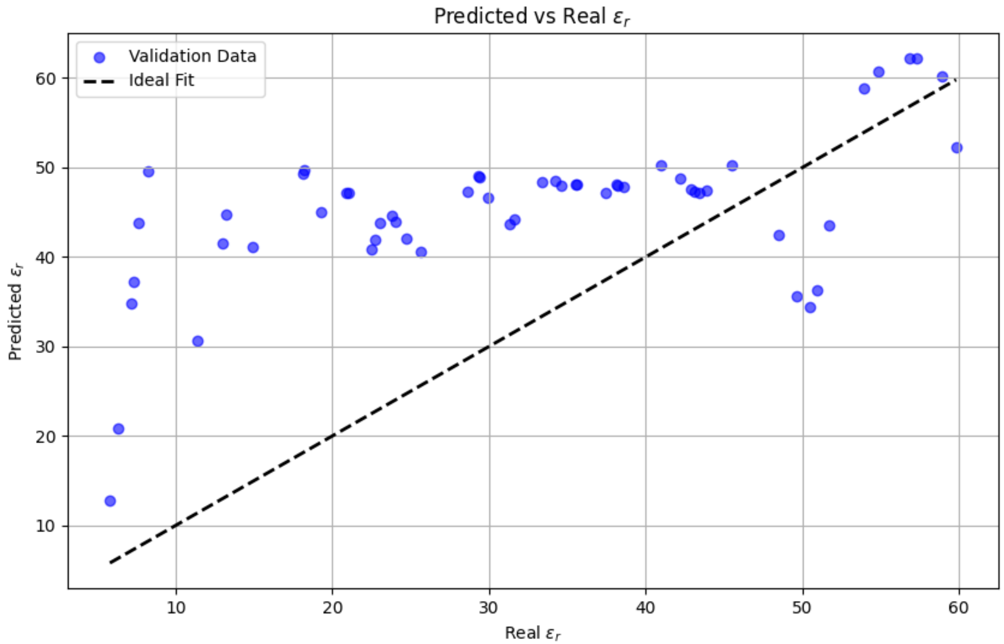
```python
model = nn.Sequential(
            # first block
            nn.Conv1d(in_channels=in_channels,
                    out_channels=num_hidden_neurons,
                    kernel_size=3, # how big is the square that's going ove
                    stride=1, # default
                    padding=1),# options = "valid" (no padding) or "same" (
            nn.ReLU(),
            nn.MaxPool1d(kernel_size=2,
                        stride=2),
            # regressor
            nn.Flatten(),
            # Where did this in_features shape come from?
            # It's because each layer of our network compresses and change
            # the max pooling layer with kernel_size=2 and stride=2 reduce
            nn.Linear(in_features=num_hidden_neurons*(sequence_length//2),
                    out_features=OUT_FEATURES)

).to(device)
```

First dataset

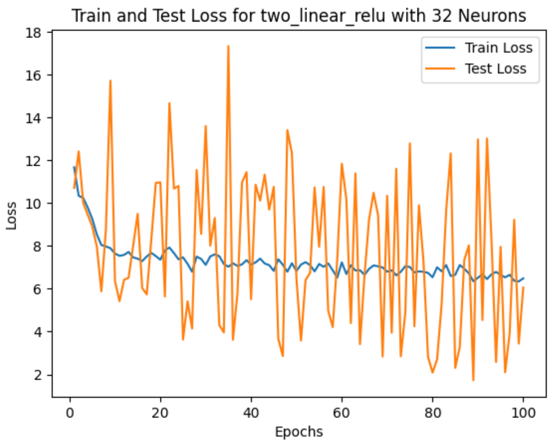


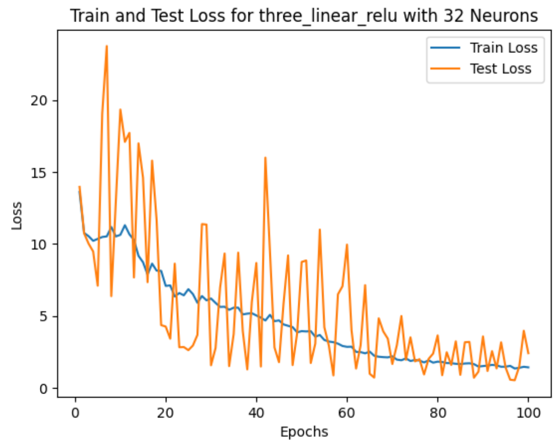


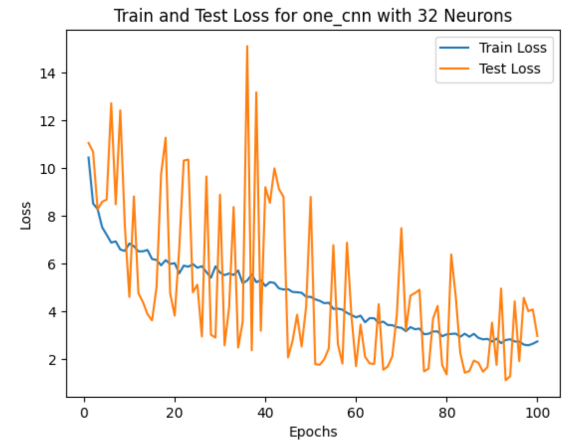


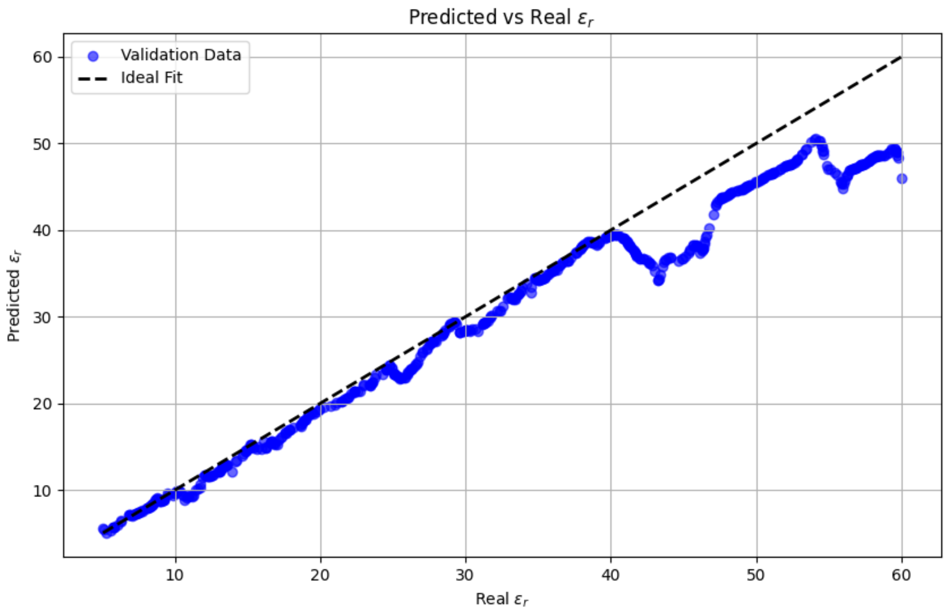


Second dataset

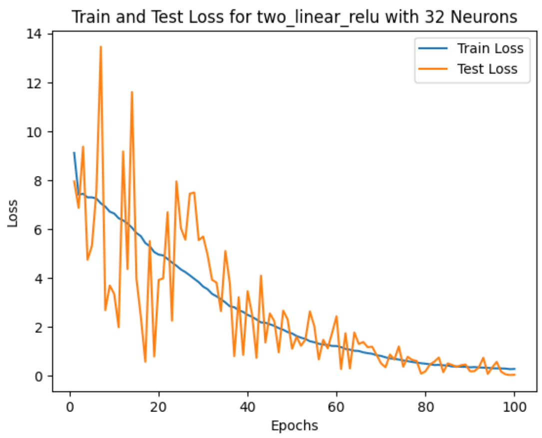


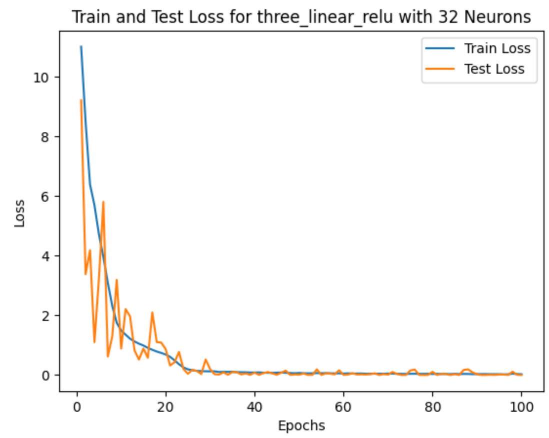


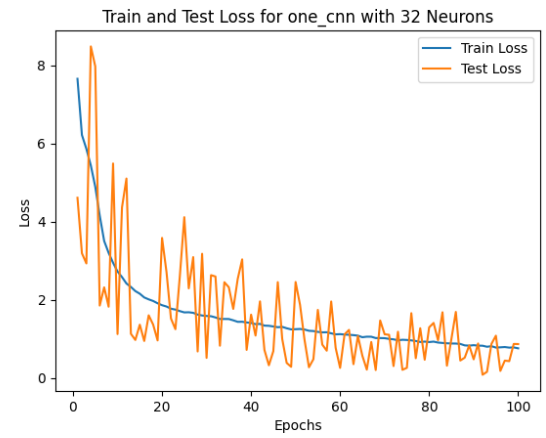


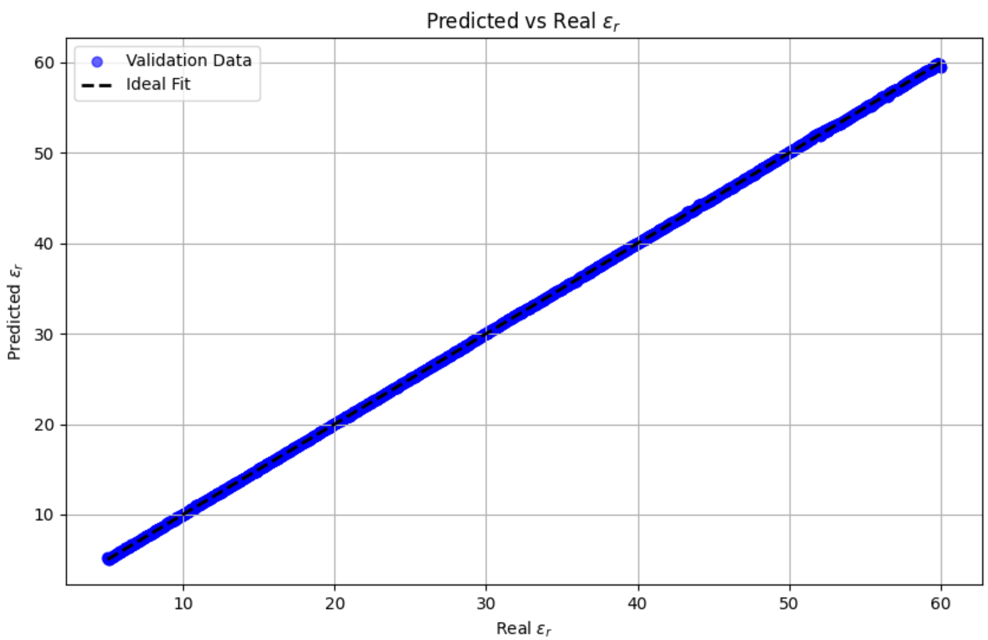


Third dataset

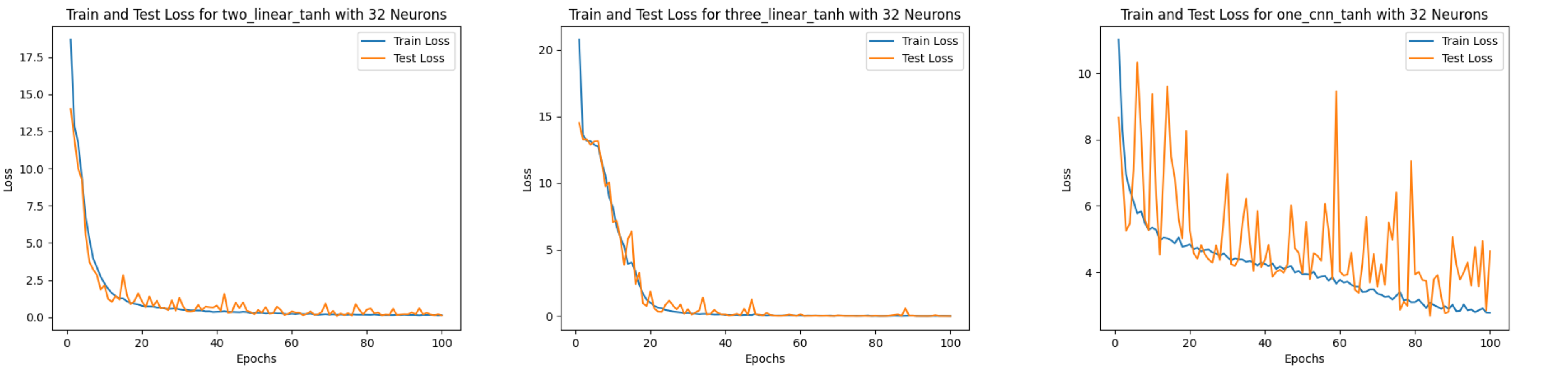


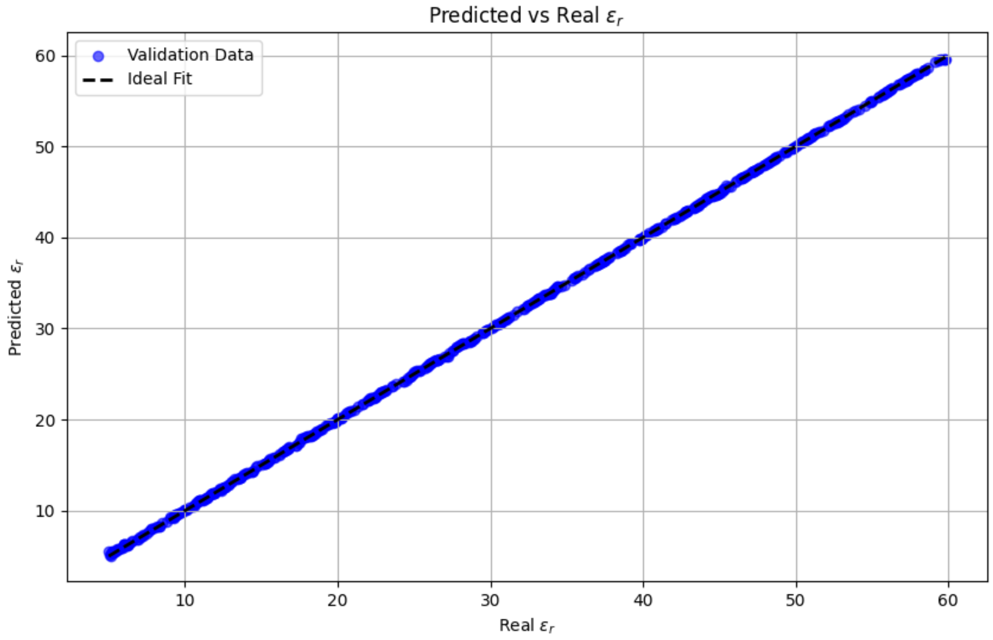






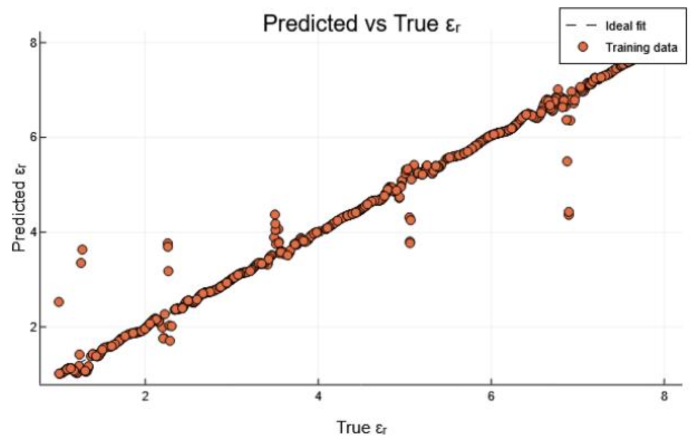
Using tanh as activation function

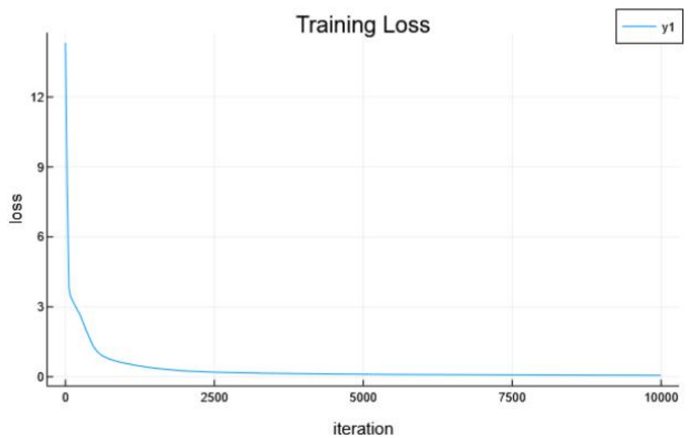


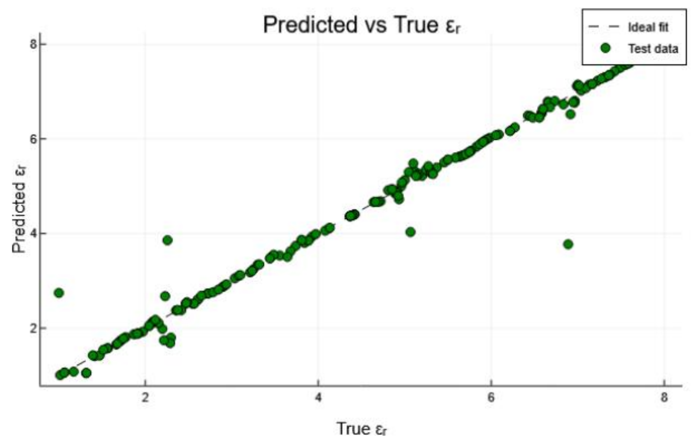


Another approach, single frequency

- Loss: $\mathrm{MSE}(\varepsilon_r, \varepsilon_{r,i})$
- $\varepsilon_r \in (1, 8)$
- 1e4 iterations
- Training loss 5.31e-2
- Test loss 9.28e-2

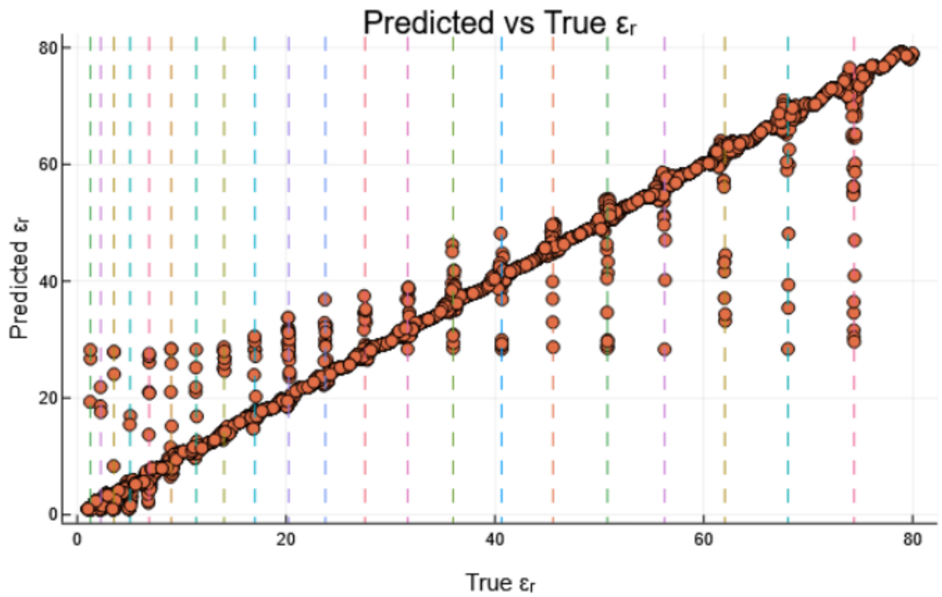


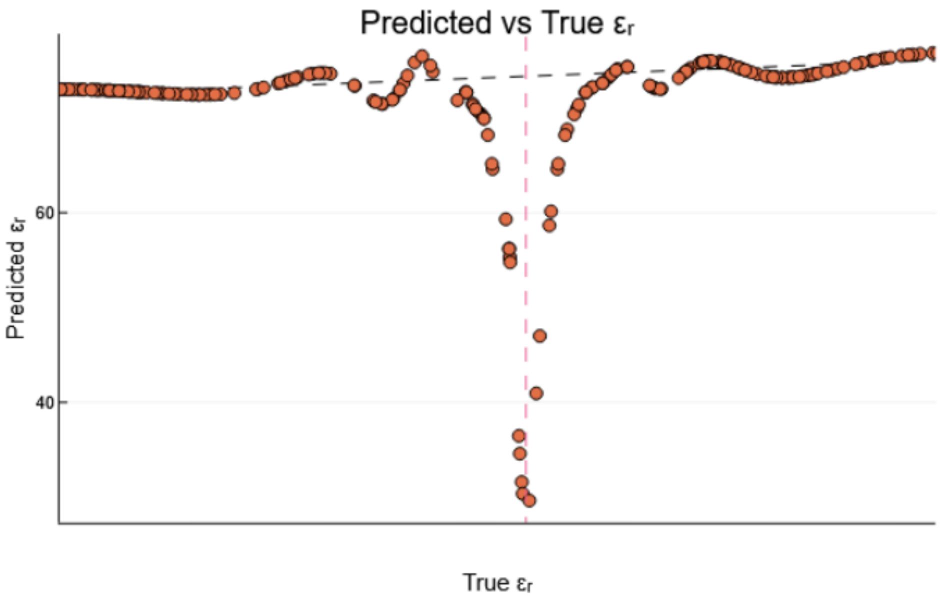




Gómez González, E. (2025).
Inverse Problems in Electromagnetics Using Autodifferentiable Solvers in Julia
Master's Thesis, Master in Multimedia and Communications, Universidad Carlos III de Madrid.

Another approach , single frequency





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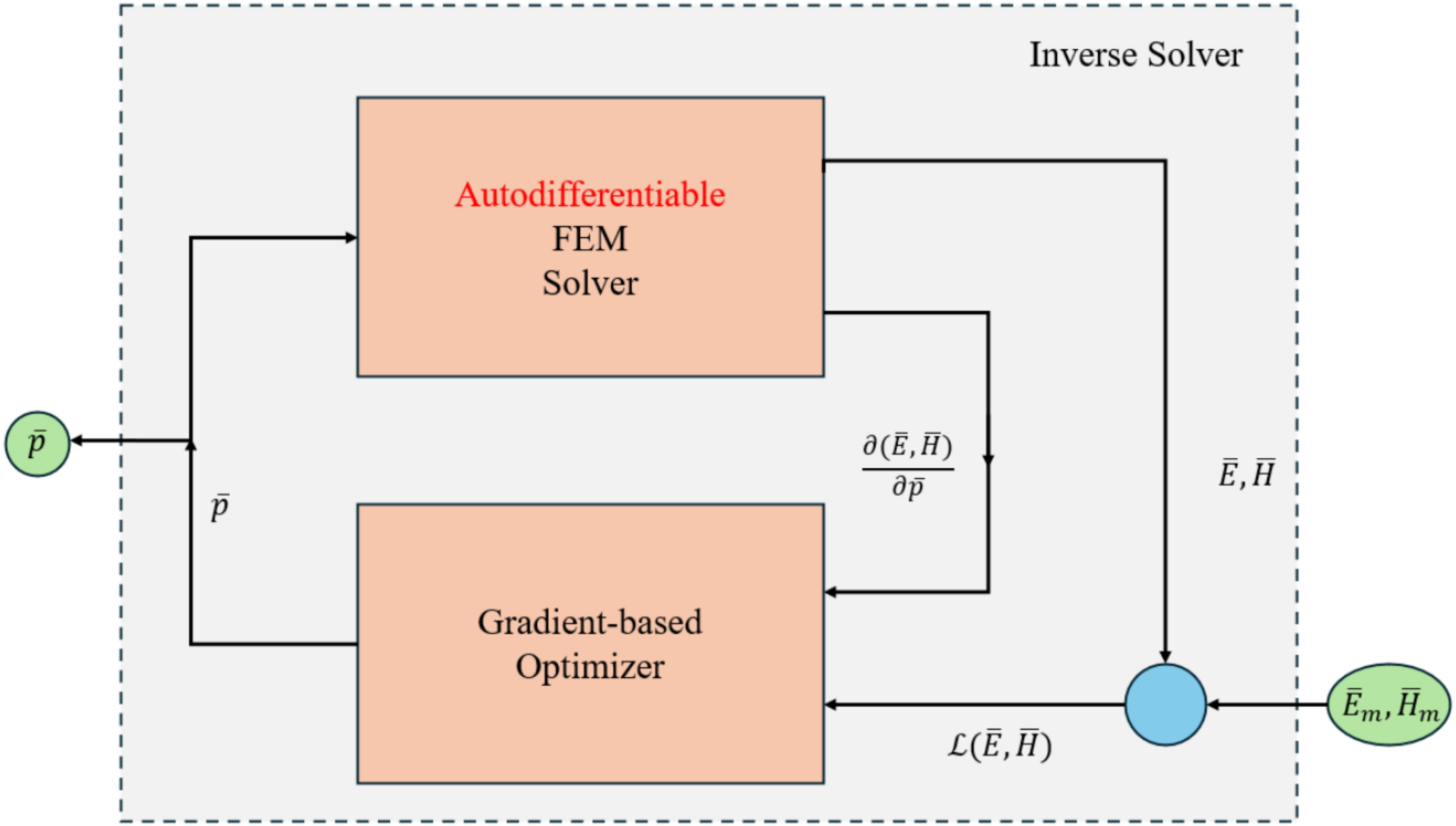
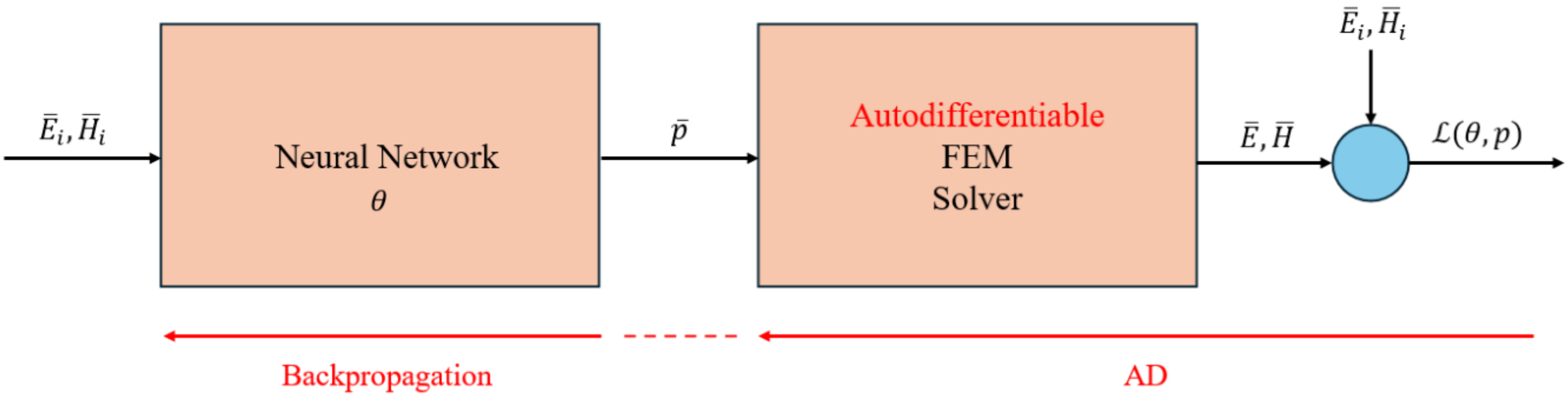
Master's Thesis, Master in Multimedia and Communications, Universidad Carlos III de Madrid.

Automatic differentiation



Gómez-González, E., Garcia-Castillo, L. E., Llorente-Romano, S., & Amor-Martin, A. (2025).
First Steps in Automatic Differentiation and Differentiable Solvers for Electromagnetics.
XL Simposio Nacional de la Unión Científica Internacional de Radio (URSI 2025), Tarragona.

Automatic differentiation (cont'd)

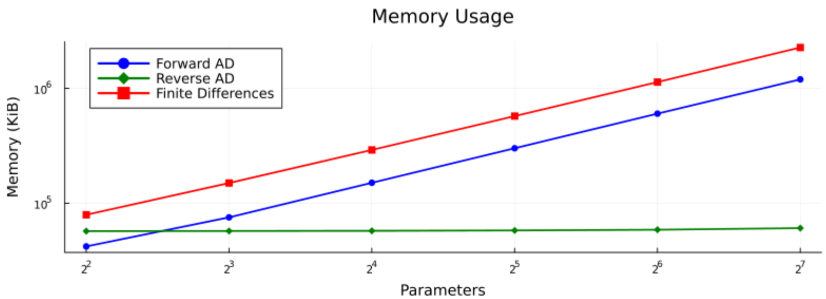


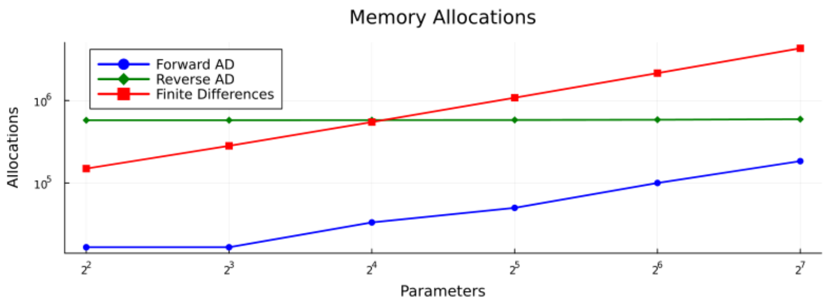
Gómez-González, E., Garcia-Castillo, L. E., Llorente-Romano, S., & Amor-Martin, A. (2025). *First Steps in Automatic Differentiation and Differentiable Solvers for Electromagnetics*. XL Simposio Nacional de la Unión Científica Internacional de Radio (URSI 2025), Tarragona.

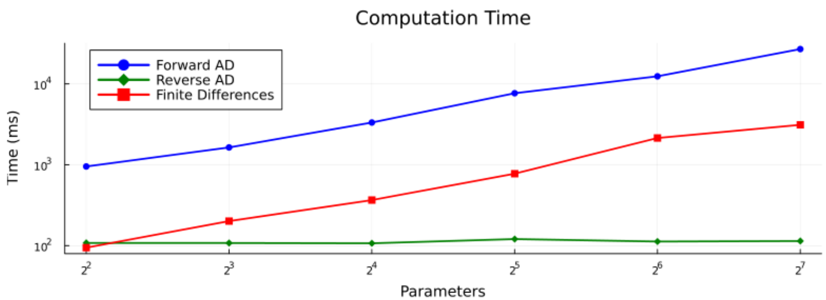
State of the art

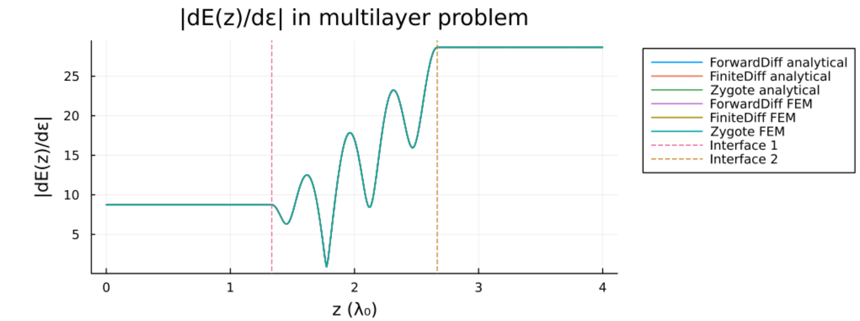
- Photonics
  - Kim, Y., Jung, A. W., Kim, S., Octavian, K., Heo, D., Park, C., Shin, J., Nam, S., Park, C., Park, J. et al. (2024). Meent: Differentiable Electromagnetic Simulator for Machine Learning
  - Hammond, A. M., Oskooi, A., Chen, M., Lin, Z., Johnson, S. G. and Ralph, S. E. (2022) High-performance hybrid time/frequency-domain topology optimization for large-scale photonics inverse design. Optics Express, 30(3), 4467–4491
  - Schubert, F., Mahlau, Y., Bethmann, K., Hartmann, F., Caspary, R., Munderloh, M., Ostermann, J. and Rosenhahn, B. (2025) Quantized inverse design for photonic integrated circuits. ACS Omega, 10, 5080–5086
- Integral equation
  - Balasubramanian, M. and Werner, D. H. (2025) Accelerated antenna design methodology using a hessian-based nonlinear optimizer with automatic differentiation. IEEE Transactions on Antennas and Propagation, 73(9), 6928–6942
  - Henry, V., Merlini, D. and Andriulli, F. (2025) Laplacian surrogate of the efie with ambitbf. In URSI EMTS 2025 – International Symposium on Electromagnetic Theory.

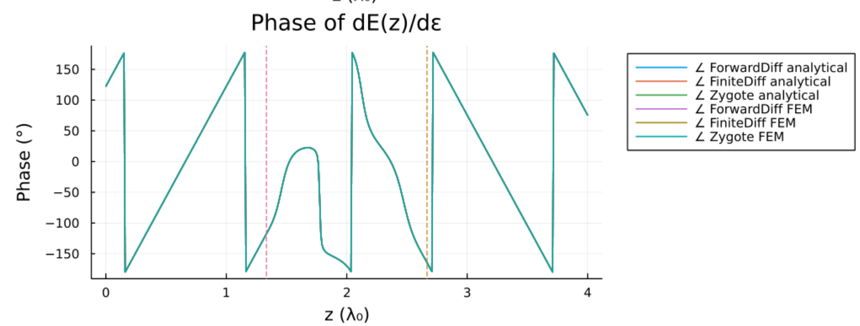
Reverse AD











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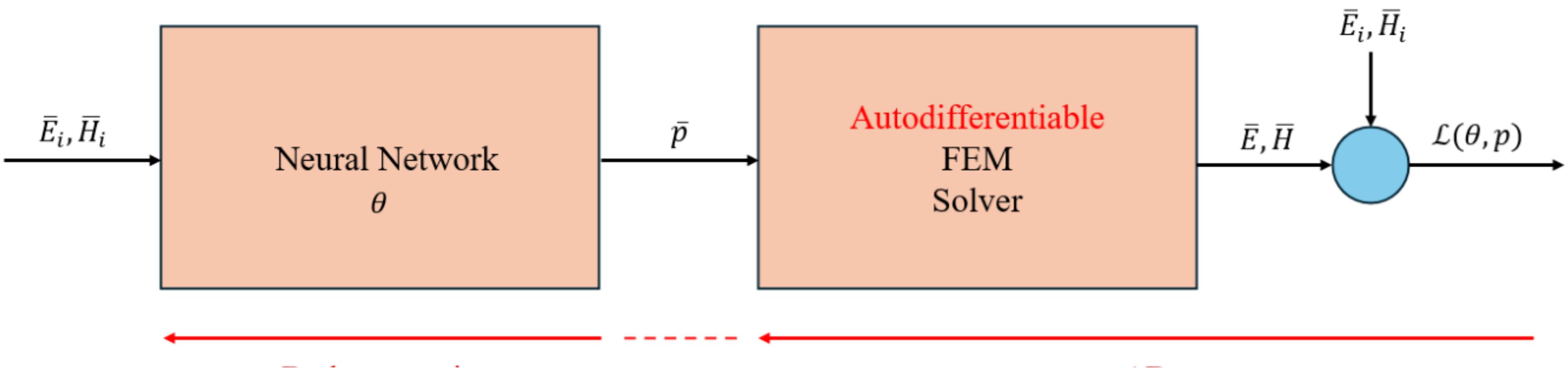
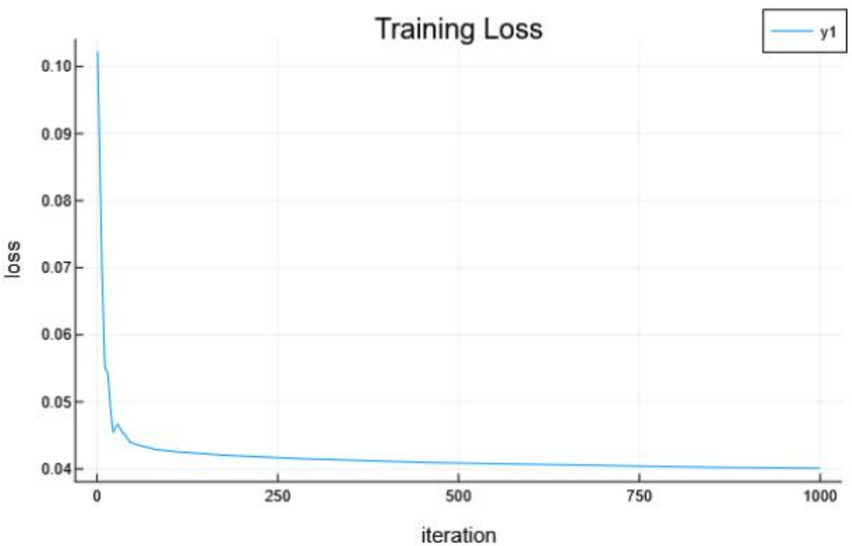
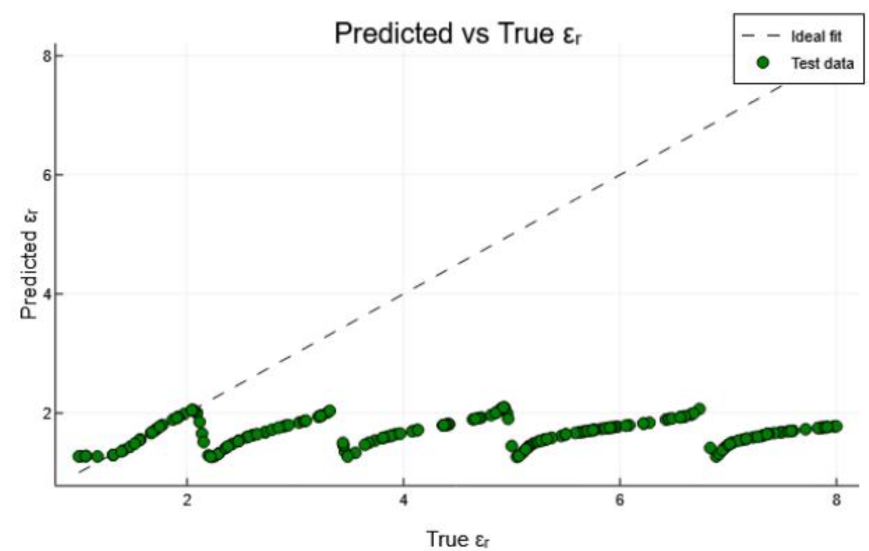
Same problem with AD







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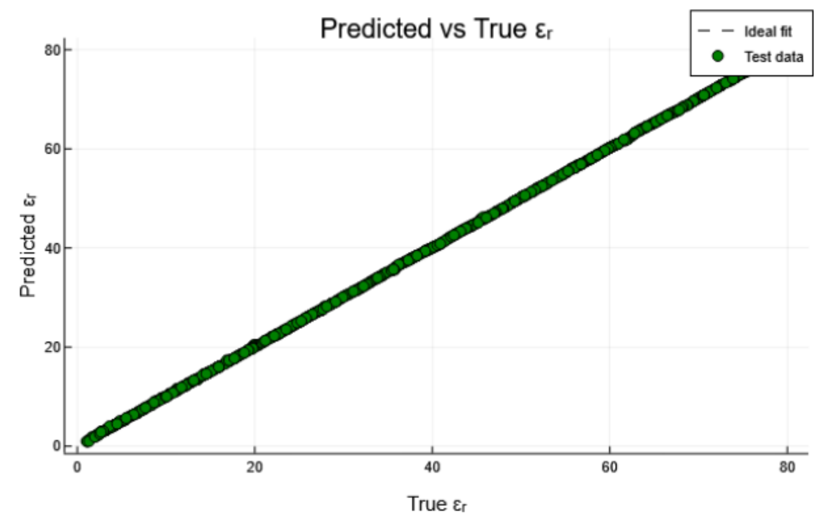
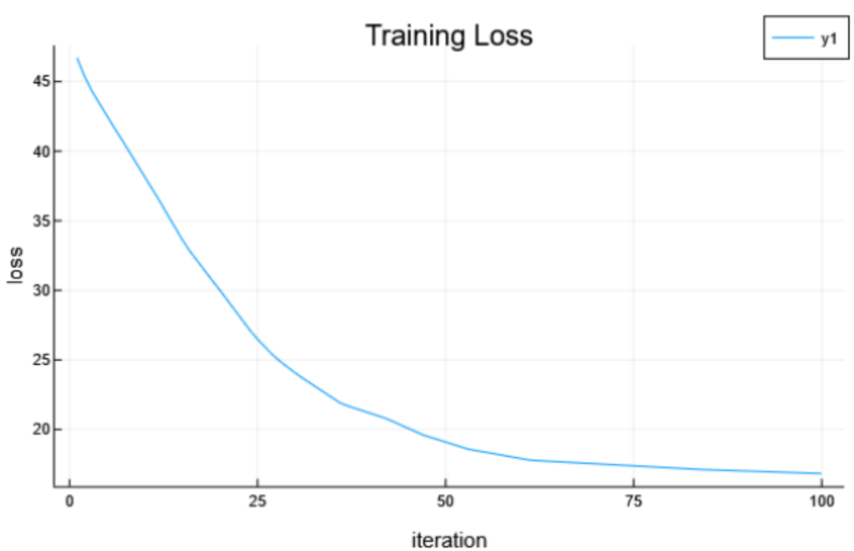
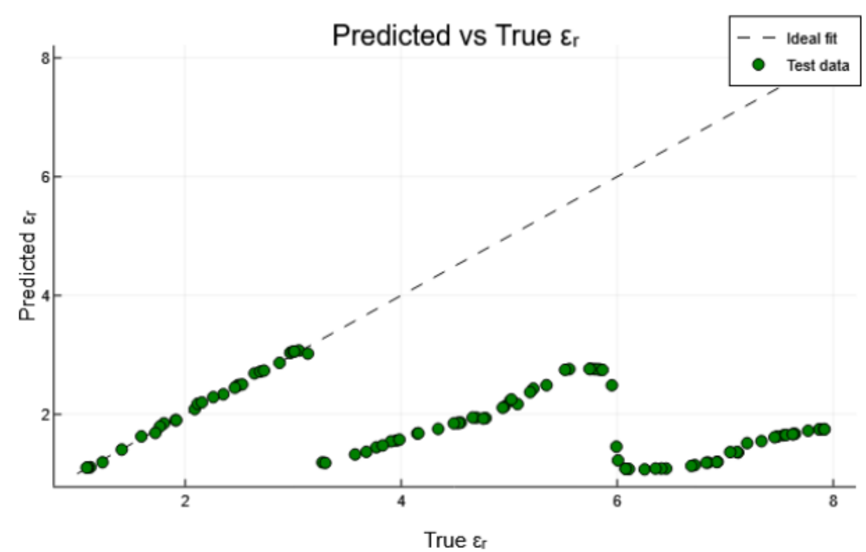
Another approach: using field values







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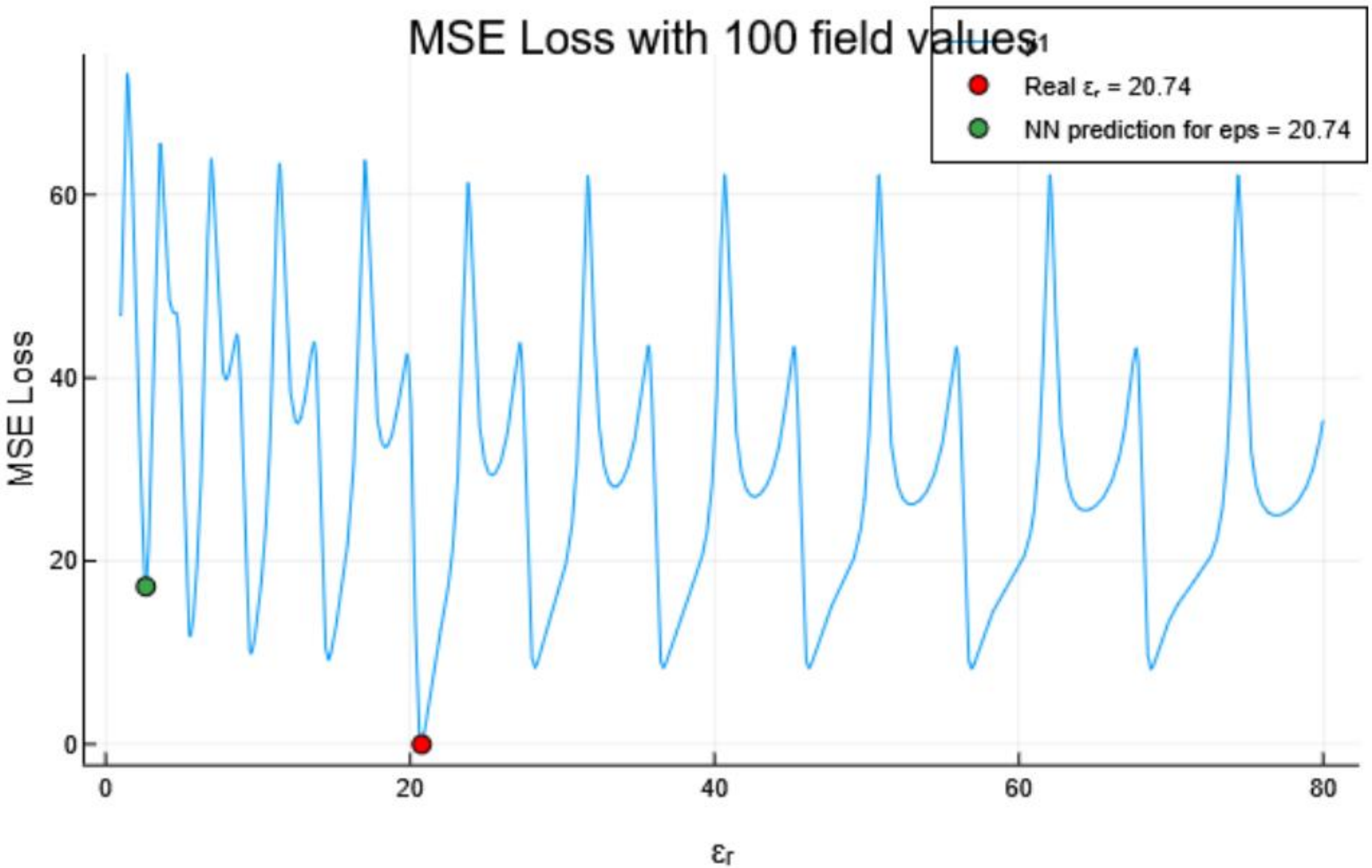
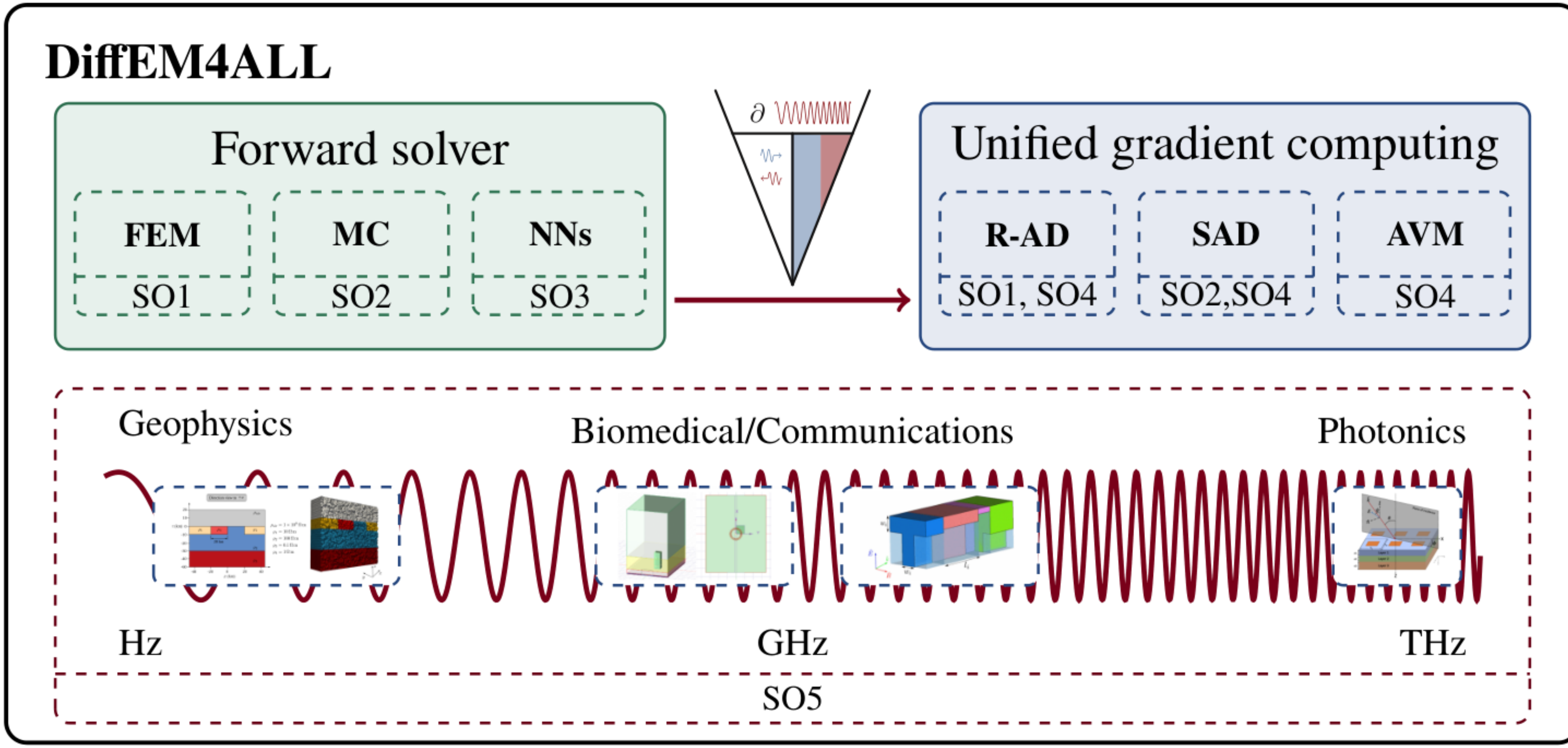
Gradient-based approaches



Gómez-González, E., Garcia-Castillo, L. E., Llorente-Romano, S., & Amor-Martin, A. (2025). *First Steps in Automatic Differentiation and Differentiable Solvers for Electromagnetics*. XL Simposio Nacional de la Unión Científica Internacional de Radio (URSI 2025), Tarragona.

Contents

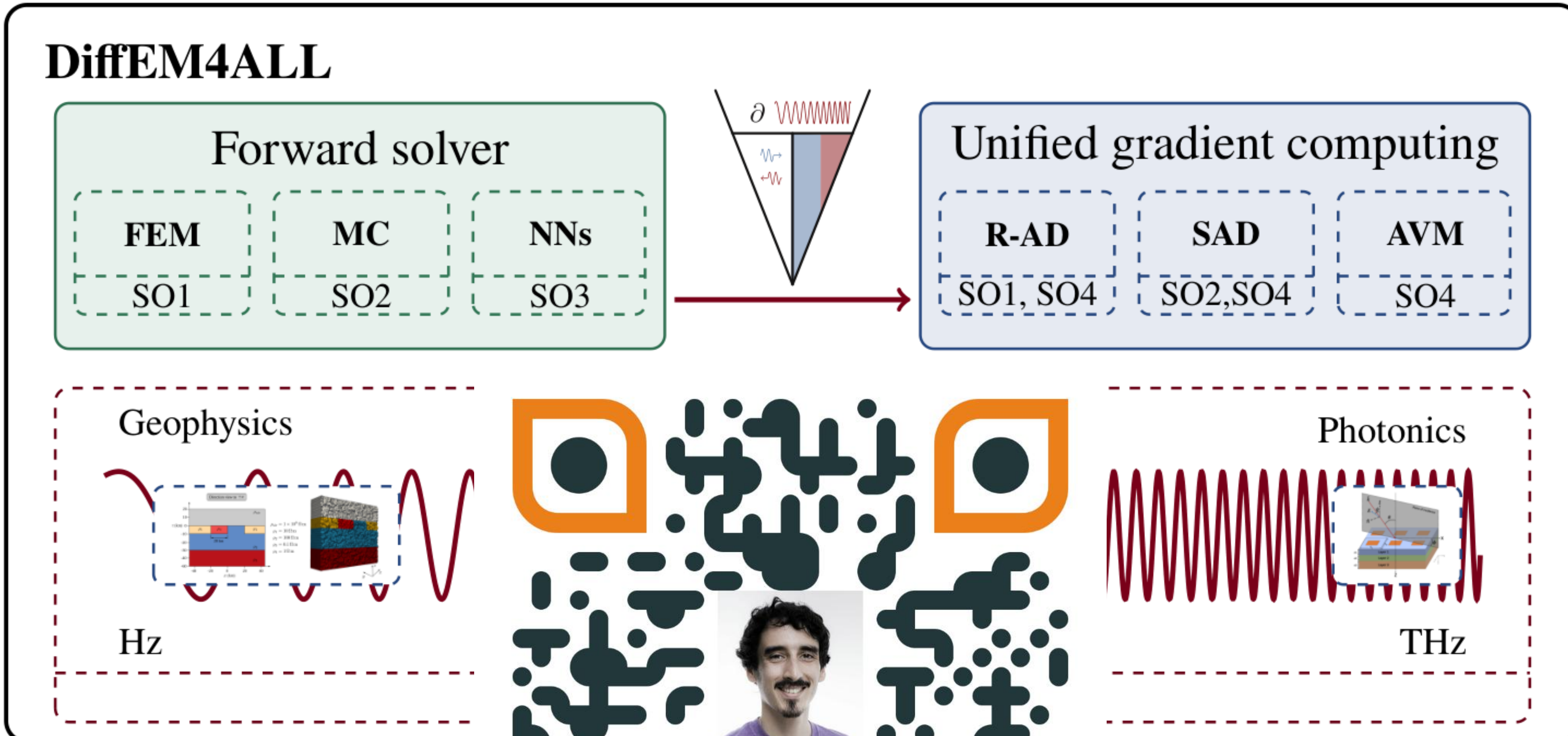
DiffEM4ALL



Main objective

The development of forward **Maxwell solvers from scratch** to be differentiable with the latest **AD** techniques, ensuring HPC-ready scalability required to tackle real-world problems and use them for the **inverse multilayer problem** as the unifying test case from Hz to THz.

DiffEM4ALL



Main objective

The development of forwar… …rentiable with the latest **AD** techniques, ensuring HPC-re… …roblems and use them for the **inverse multilayer problem**…