



PINNs for the time-domain Maxwell equations - Preliminary results

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PINNs for the time-domain Maxwell equations

Preliminary results

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- 1 Objectives of the study
- 2 Mathematical model
- 3 PINN formulation
- 4 Results using DeepXDE
CHECK OUR TUTORIAL “A Short Introduction to Physics-Informed Neural Networks” TOMORROW!
 - Standing wave in a metallic cavity : homogeneous material case
 - Standing wave in a metallic cavity : heterogeneous material case
- 5 Closure

Motivations

- Surrogate models : ultra-fast electromagnetic solvers
- Include physical and geometrical parameters in addition to space and time/frequency ones
- Main target : inverse design of large-scale photonic devices

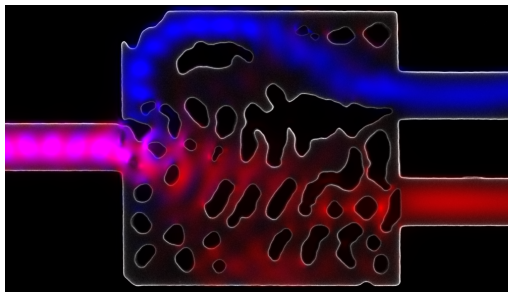


Figure: A compact demultiplexer for telecommunications wavelengths.¹

¹Source: <https://nqp.stanford.edu/inverse-design-photonics>

Roadmap

- ① Evaluate PINN approach for electromagnetic wave propagation (Maxwell equations)
 - Time-domain formulation
 - Frequency-domain formulation
- ② Identify possible directions of methodological improvement
 - Training point sampling strategy
 - Activation function formulation
 - Network topology
 - Other routes : transfer learning, tensor-compressed training, adaptive strategies, etc.
- ③ Extend PINN models to the nanophotonics setting

Model and IBV problem: the 3D case

Maxwell equations, $\mathbf{x} \in \Omega$, $t > 0$

$$\begin{cases} \varepsilon \partial_t \mathbf{E} - \nabla \times \mathbf{H} = 0 \\ \mu \partial_t \mathbf{H} + \nabla \times \mathbf{E} = 0 \end{cases}$$
$$\mathbf{E} = \mathbf{E}(\mathbf{x}, t) \quad \text{and} \quad \mathbf{H} = \mathbf{H}(\mathbf{x}, t)$$

Boundary conditions: $\partial\Omega = \Gamma_a \cup \Gamma_m$

$$\begin{cases} \mathbf{n} \times \mathbf{E} = 0 \text{ on } \Gamma_m \text{ (metallic boundary)} \\ \mathbf{n} \times \mathbf{E} - \sqrt{\frac{\mu}{\varepsilon}} \mathbf{n} \times (\mathbf{H} \times \mathbf{n}) = \mathbf{n} \times \mathbf{E}_{\text{inc}} - \sqrt{\frac{\mu}{\varepsilon}} \mathbf{n} \times (\mathbf{H}_{\text{inc}} \times \mathbf{n}) \text{ on } \Gamma_a \text{ (absorbing boundary)} \end{cases}$$

where $(\mathbf{E}_{\text{inc}}, \mathbf{H}_{\text{inc}})$ is a given incident field.

Initial conditions

$$\mathbf{E}_0 = \mathbf{E}(\mathbf{x}, 0) \quad \text{and} \quad \mathbf{H}_0 = \mathbf{H}(\mathbf{x}, 0)$$

Transverse Magnetic mode (TM_z)

$$\mathbf{H} = {}^t(H_x, H_y, 0), \mathbf{E} = {}^t(0, 0, E_z)$$

$$\begin{cases} \varepsilon \frac{\partial E_z}{\partial t} - \frac{\partial H_y}{\partial x} + \frac{\partial H_x}{\partial y} = 0, \\ \mu \frac{\partial H_x}{\partial t} + \frac{\partial E_z}{\partial y} = 0 \\ \mu \frac{\partial H_y}{\partial t} - \frac{\partial E_z}{\partial x} = 0 \end{cases}$$

General framework

$$\begin{cases} \frac{\partial u(\mathbf{x}, t)}{\partial t} + \mathcal{N}[u(\mathbf{x}, t); \lambda] &= 0, \quad \mathbf{x} \in \Omega \subset \mathbb{R}^d, \quad t \in [0, T] \\ u(\mathbf{x}, t) &= g(\mathbf{x}, t), \quad \mathbf{x} \in \partial\Omega, \quad t \in [0, T] \\ u(\mathbf{x}, 0) &= h(\mathbf{x}), \quad \mathbf{x} \in \Omega, \quad t = 0 \end{cases}$$

where $\mathcal{N}[u(\mathbf{x}, t); \lambda]$ is a differential operator parametrized by λ ,^a and $u(\mathbf{x}, t)$ is the solution.

Let u_θ be the NN prediction for u and $f(\mathbf{x}, t; \theta, \lambda) := \frac{\partial}{\partial t} u_\theta(\mathbf{x}, t) + \mathcal{N}[u_\theta(\mathbf{x}, t); \lambda]$.

Let also $\{\mathbf{x}_i, t_i\}_{i=1}^{N_f} \in \Omega \times [0, T]$.

- Residual part of the loss function : $\mathcal{L}_f(\theta, \lambda) = \frac{1}{N_f} \sum_{i=1}^{N_f} |f(\mathbf{x}_i, t_i; \theta, \lambda)|^2$
- Data loss for initial and boundary conditions : $\mathcal{L}_u(\theta) = \frac{1}{N_u} \sum_{i=1}^{N_u} |u_\theta(\mathbf{x}_i, t_i) - u_i^*|^2$

where $\{\mathbf{x}_i, t_i, u_i^*\}_{i=1}^{N_u}$ denotes the initial and boundary training data on $u(\mathbf{x}, t)$.

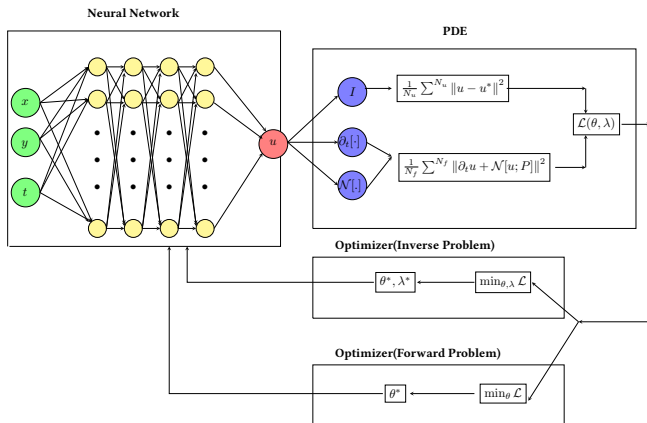
^aFor direct problems λ is (in general) specified.

General framework: problem statement (NN training)

Find the parameters θ (and λ in the inverse case) which minimizes the loss function

$$\mathcal{L}(\theta, \lambda) = w_f \mathcal{L}_f(\theta, \lambda) + w_u \mathcal{L}_u(\theta)$$

where w_f and w_u are loss weights.



Standing wave in a metallic cavity : homogeneous material case

- Material is taken to be the vacuum, i.e., $\varepsilon = \mu = 1^a$
- The computational domain is defined by $\Omega = [0, 1] \times [0, 1]$
- Time window for the training is $[0, 2\pi]^b$
- Exact time-domain solution

$$\begin{cases} H_x = \frac{-\pi}{\omega} \sin(\pi x) \cos(\pi y) \sin(\omega t) \\ H_y = \frac{\pi}{\omega} \cos(\pi x) \sin(\pi y) \sin(\omega t) \\ E_z = \sin(\pi x) \sin(\pi y) \cos(\omega t) \end{cases}$$

with $\omega = \pi\sqrt{2}$.

- Boundary condition: $E_z = 0$
- Electromagnetic field at the time $t = 0$ for $(x, y) \in [0, 1] \times [0, 1]$

$$H_x = H_y = 0, \quad E_z = \sin(\pi x) \sin(\pi y)$$

^aRelative quantities.

^bRenormalized units.

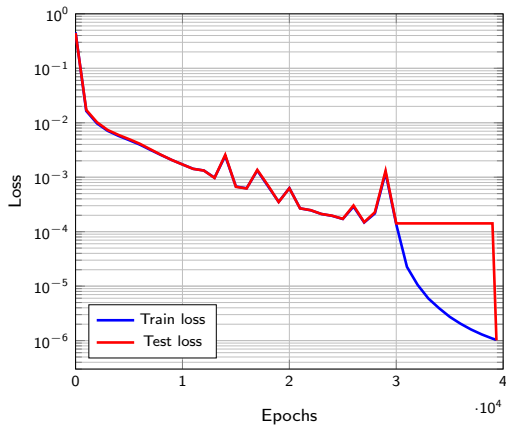
Results using DeepXDE

Standing wave in a metallic cavity (homogeneous material case)

- Numbers of random sample points are $N_0 = 400$, $N_b = 400$ and $N_f = 2000$
- Network structure: 3 inputs (x, y, t) , 3 outputs (E_z, H_x, H_y) , 4 hidden layers and 50 neurons per layer
- Nonlinear activation function: hyperbolic tangent \tanh
- The model is first trained for 10 000 iterations using Adam optimizer with learning rate set to 0.001
- L-BFGS optimizer is then used to improve the convergence

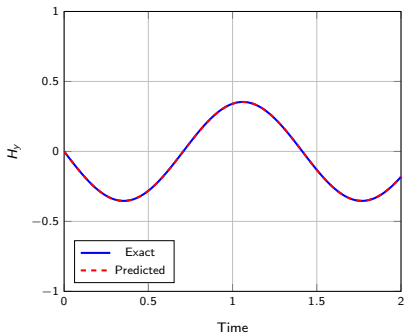
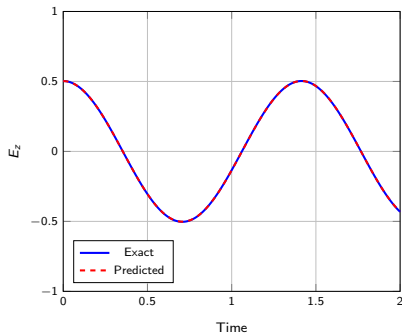
Results using DeepXDE

Standing wave in a metallic cavity (homogeneous material case)



Results using DeepXDE

Standing wave in a metallic cavity (homogeneous material case)



Solutions at $x = 0.75$ m and $y = 0.75$

Results using DeepXDE

Standing wave in a metallic cavity (homogeneous material case)

	L_2 errors	4×20	4×50
$t_0 = 0.25$	$\mathcal{L}_{2,E_z}(t_0)$	$7.6 \cdot 10^{-3}$	$2.2 \cdot 10^{-3}$
	$\mathcal{L}_{2,H_x}(t_0)$	$5.8 \cdot 10^{-3}$	$1.6 \cdot 10^{-3}$
	$\mathcal{L}_{2,H_y}(t_0)$	$5.3 \cdot 10^{-3}$	$1.4 \cdot 10^{-3}$
$t_1 = 1$	$\mathcal{L}_{2,E_z}(t_1)$	$2.3 \cdot 10^{-2}$	$7.2 \cdot 10^{-3}$
	$\mathcal{L}_{2,H_x}(t_1)$	$1.1 \cdot 10^{-2}$	$5.5 \cdot 10^{-3}$
	$\mathcal{L}_{2,H_y}(t_1)$	$1.2 \cdot 10^{-2}$	$3.2 \cdot 10^{-3}$

Relative L_2 errors of E_z , H_x and H_y for two network configurations (4×20 and 4×50)

Standing wave in a metallic cavity : heterogeneous material case

- The computational domain is defined by $\Omega = [0, \frac{5}{4}] \times [0, 1]$
- $\varepsilon = \varepsilon_2$ if $0 \leq x \leq \frac{1}{2}$ and $0 \leq y \leq 1$, and $\varepsilon = \varepsilon_1$ if $\frac{1}{2} \leq x \leq \frac{5}{4}$ and $0 \leq y \leq 1$
- Exact time-domain solution

$$E_z = \begin{cases} \sin(a_1 x) \sin(by) \sin(\omega t), & 0 \leq x \leq \frac{1}{2} \quad 0 \leq y \leq 1 \\ \cos(a_2 x) \sin(by) \sin(\omega t), & \frac{1}{2} \leq x \leq \frac{5}{4} \quad 0 \leq y \leq 1 \end{cases}$$

$$H_y = \begin{cases} -\frac{a_1}{\omega} \cos(a_1 x) \sin(by) \cos(\omega t), & 0 \leq x \leq \frac{1}{2} \quad 0 \leq y \leq 1 \\ \frac{a_2}{\omega} \sin(a_2 x) \sin(by) \cos(\omega t), & \frac{1}{2} \leq x \leq \frac{5}{4} \quad 0 \leq y \leq 1 \end{cases}$$

$$H_x = \begin{cases} \frac{b}{\omega} \sin(a_1 x) \cos(by) \cos(\omega t), & 0 \leq x \leq \frac{1}{2} \quad 0 \leq y \leq 1 \\ -\frac{b}{\omega} \cos(a_2 x) \cos(by) \cos(\omega t), & \frac{1}{2} \leq x \leq \frac{5}{4} \quad 0 \leq y \leq 1 \end{cases}$$

where $\varepsilon_1 = 1, \varepsilon_2 = 2, a_1 = 3\pi, a_2 = 2\pi, b = \pi$, and $\omega = \sqrt{5}\pi$.

Standing wave in a metallic cavity : heterogeneous material case

- The computational domain is defined by $\Omega = [0, \frac{5}{4}] \times [0, 1]$
- $\varepsilon = \varepsilon_2$ if $0 \leq x \leq \frac{1}{2}$ and $0 \leq y \leq 1$, and $\varepsilon = \varepsilon_1$ if $\frac{1}{2} \leq x \leq \frac{5}{4}$ and $0 \leq y \leq 1$
- Time window for the training is $[0, 2\pi]^a$
- Boundary condition: $E_z = 0$
- Electromagnetic field at the time $t = 0$ for $(x, y) \in \Omega$ computed from exact solution

^aRenormalized units.

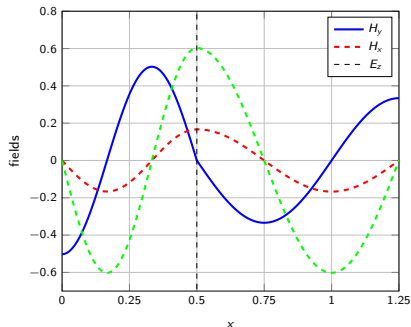
Results using DeepXDE

Standing wave in a metallic cavity (heterogeneous material case)

- Numbers of random sample points are $N_0 = 1000$, $N_b = 500$ and $N_f = 5000$
- Network structure: 3 inputs (x, y, t) , 3 outputs (E_z, H_x, H_y) , 4 hidden layers and 80 neurons per layer
- Nonlinear activation function: hyperbolic tangent \tanh
- The model is first trained for 30 000 iterations using Adam optimizer with learning rate set to 0.001
- L-BFGS optimizer is then used to improve the convergence

Results using DeepXDE

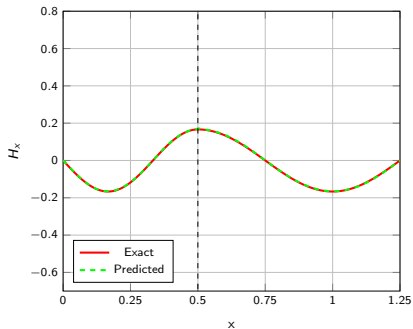
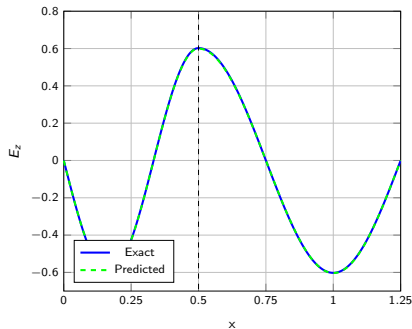
Standing wave in a metallic cavity (heterogeneous material case)



Plots of the analytical solution along the line $y = 0.75$ at time $t = 0.75$ m

Results using DeepXDE

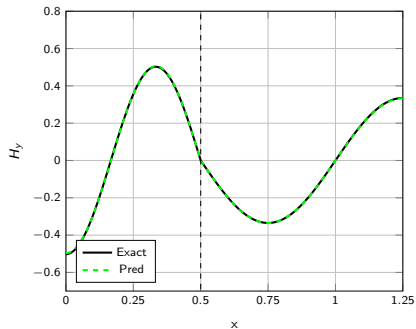
Standing wave in a metallic cavity (heterogeneous material case)



Solutions at $t = 0.75$ m and $y = 0.75$.

Results using DeepXDE

Standing wave in a metallic cavity (heterogeneous material case)



Solutions at $t = 0.75$ m and $y = 0.75$.

Results using DeepXDE

Standing wave in a metallic cavity (heterogeneous material case)

Number of training points	Error on E_z	Error on H_x	Error on H_y	CPU (mn)
1000	$1.38 \cdot 10^{-2}$	$2.08 \cdot 10^{-2}$	$1.33 \cdot 10^{-2}$	19
2500	$7.73 \cdot 10^{-3}$	$1.53 \cdot 10^{-2}$	$9.37 \cdot 10^{-3}$	28
4000	$7.43 \cdot 10^{-3}$	$1.14 \cdot 10^{-2}$	$7.48 \cdot 10^{-3}$	35
5000	$4.88 \cdot 10^{-3}$	$8.60 \cdot 10^{-3}$	$5.35 \cdot 10^{-3}$	40

Relative L_2 errors of E_z, H_x and H_y with different training points

- Extension to 3D case
- PINNs formulation for parameterized problems
- Interpolation versus extrapolation in output predictions
- Detailed performance study
- CPU versus GPU acceleration

Thank you!

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