EMC Forum

Reinventing Electromagnetic Simulation with Physics-Informed AI

Mohamed Kheir
kheir@sdu.dk

29.06.2026

SDU

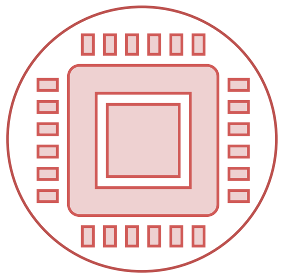
Agenda

E M C Forum

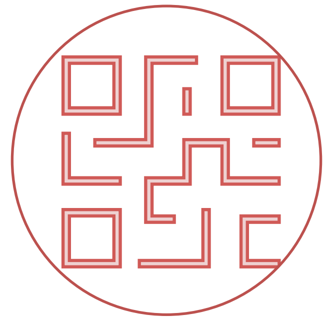
- Introduction and Problem Statement.
- Traditional AI/ML for EMI.
- Introducing Physics-Informed Neural Networks (PINNs/PIML).
- Kolmogorov-Arnold-Network (KAN)-Based PIML.
- PINN-Driven EMI Simulations.
- Conclusions.

Introduction

Electronic devices cause different forms of EMI



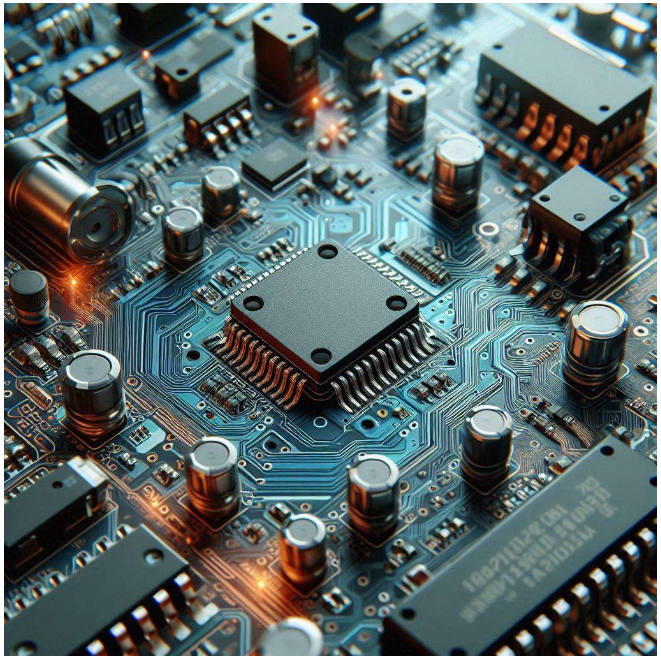
A single PCB employs different connectivity standards and therefore emissions increase

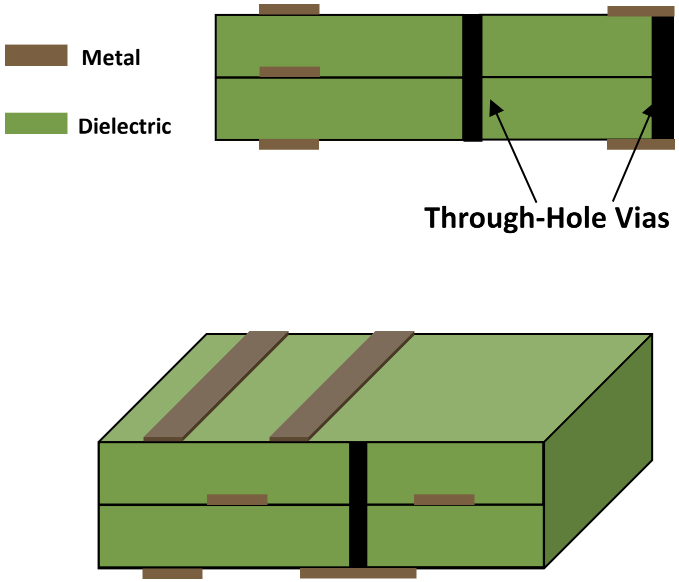


Most EMI issues originate from PCBs and radiate into free-space or couple into other parts of the circuit

Simulating such PCB is needed in the early-stage of product design and can be helpful in detecting any potential problems

Printed Curcuit Boards (PCBs)





A Multilayer PCB

PCBs are often the major contributor to EMI emissions!

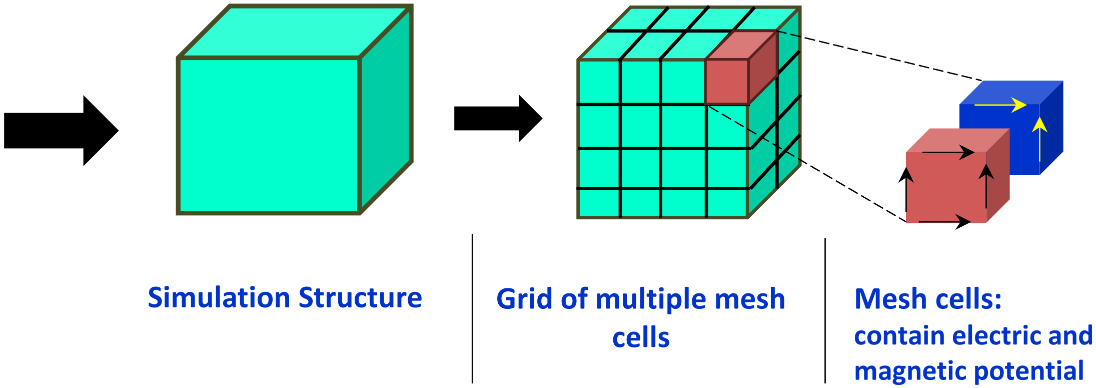
How Do Full-Wave Simulation Engines Work?

$$\oint_{\partial A} \vec{E} \cdot d\vec{s} = -\iint \frac{\partial \vec{B}}{\partial t} \cdot d\vec{A}$$

$$\oint_{\partial A} \vec{H} \cdot d\vec{s} = \iint \left(\frac{\partial \vec{D}}{\partial t} + \vec{J} \right) \cdot d\vec{A}$$

$$\oint_{\partial V} \vec{D} \cdot d\vec{A} = \iiint \rho \, dV$$

$$\oint_{\partial V} \vec{B} \cdot d\vec{A} = 0$$



Maxwell's Equations

Discretization Process

Issues with Full-Wave Simulations

Simulation Time: Full-wave simulations require long time to solve Maxwell's equations for any EMC problem.

Computational Capacity: A typical EMC problem needs high-speed multi-core processors with very high RAM capacity and additionally a couple of GPU cards. This makes the machine very expensive.

Energy Consumption: Long computation time on a highly-equipped machine typically consumes a huge amount of electrical energy and cooling additionally.

Iterations: Most EMI problem requires several iterative simulations to reach a trouble-shooting since they are not clearly detectable with standard straightforward techniques.

Physics-Informed Machine Learning (PIML)

EMC Forum

- Multi-layer perceptrons (MLPs), which consist of neurons connected via trainable weights, are the standard building blocks of neural networks.

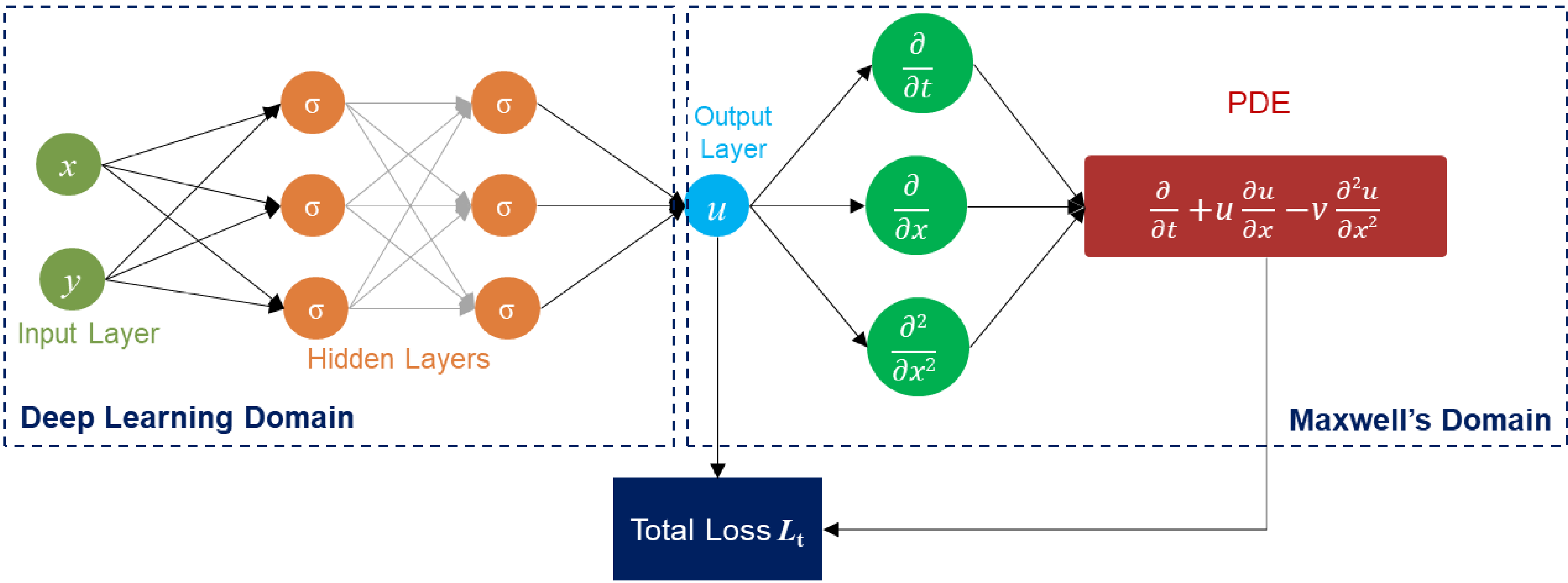
- **PIML integrates data and mathematical physics models, even in partially understood, uncertain and high-dimensional contexts*.**

- PIML combines two learning methods: 1) surrogate approximation, and 2) PDE learning network.

- The PDE learning part of the loss function is derived in the form of a residual function and can be considered as an unsupervised learning.

*Karniadakis, G.E., Kevrekidis, I.G., Lu, L. *et al.* Physics-informed machine learning. *Nat Rev Phys* **3**, 422–440 (2021).

Physics-Informed Machine Learning



What is Kolmogorov-Arnold-Network (KAN)?

EMC Forum

- Recently introduced by a group of MIT researchers inspired by the Kolmogorov-Arnold representation theorem of the two great Mathematicians “**Vladimir Arnold**” and “**Andrey Kolmogorov**”.

- KANs proposes, for the first time, learnable activation functions on their edges (or “weights”).

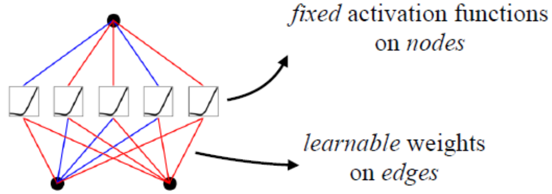
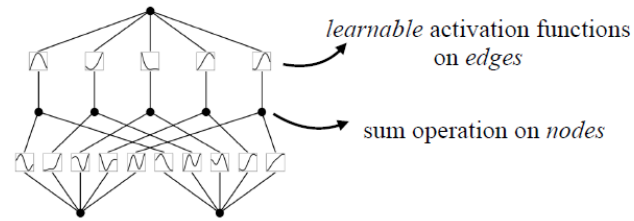
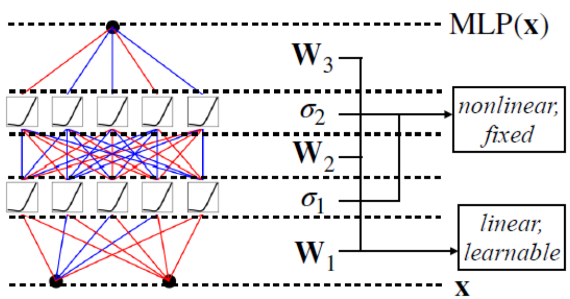
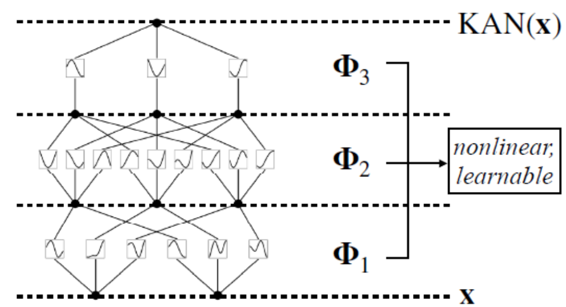
- KANs do not use linear weights at all. Instead, each weight parameter is replaced by a univariate function, which is represented as a spline.

- In the end, the KAN-based PIML can potentially represent the solution with a symbolic function in contrast to MLP training functions.

Liu, Z., Wang, Y., Vaidya, S., Ruehle, F., Halverson, J., Soljačić, M., & Tegmark, M. (2024). Kan: Kolmogorov-Arnold networks. arXiv preprint arXiv:2404.19756.

MLP vs. KAN

EMC Forum

Model	Multi-Layer Perceptron (MLP)	Kolmogorov-Arnold Network (KAN)
Theorem	Universal Approximation Theorem	Kolmogorov-Arnold Representation Theorem
Formula (Shallow)	$f(\mathbf{x}) \approx \sum_{i=1}^{N(\epsilon)} a_i \sigma(\mathbf{w}_i \cdot \mathbf{x} + b_i)$	$f(\mathbf{x}) = \sum_{q=1}^{2n+1} \Phi_q \left(\sum_{p=1}^{n} \phi_{q,p}(x_p) \right)$
Model (Shallow)	(a) 	(b) 
Formula (Deep)	$\mathrm{MLP}(\mathbf{x}) = (\mathbf{W}_3 \circ \sigma_2 \circ \mathbf{W}_2 \circ \sigma_1 \circ \mathbf{W}_1)(\mathbf{x})$	$\mathrm{KAN}(\mathbf{x}) = (\mathbf{\Phi}_3 \circ \mathbf{\Phi}_2 \circ \mathbf{\Phi}_1)(\mathbf{x})$
Model (Deep)	(c) 	(d) 

From:

Liu, Z., Wang, Y., Vaidya, S., Ruehle, F., Halverson, J., Soljačić, M., & Tegmark, M. (2024). Kan: Kolmogorov-Arnold networks. arXiv preprint arXiv:2404.19756.

PIML for EMI/EMC Simulations?

Data Integration

PIML integrates data from both domains (measurement and PDEs).

Embedding PDEs

PDEs are embedded into the loss function which enhances accuracy.

Mesh-less Simulations!

PIML can operate at any point within the calculation domain without the need for discretization.

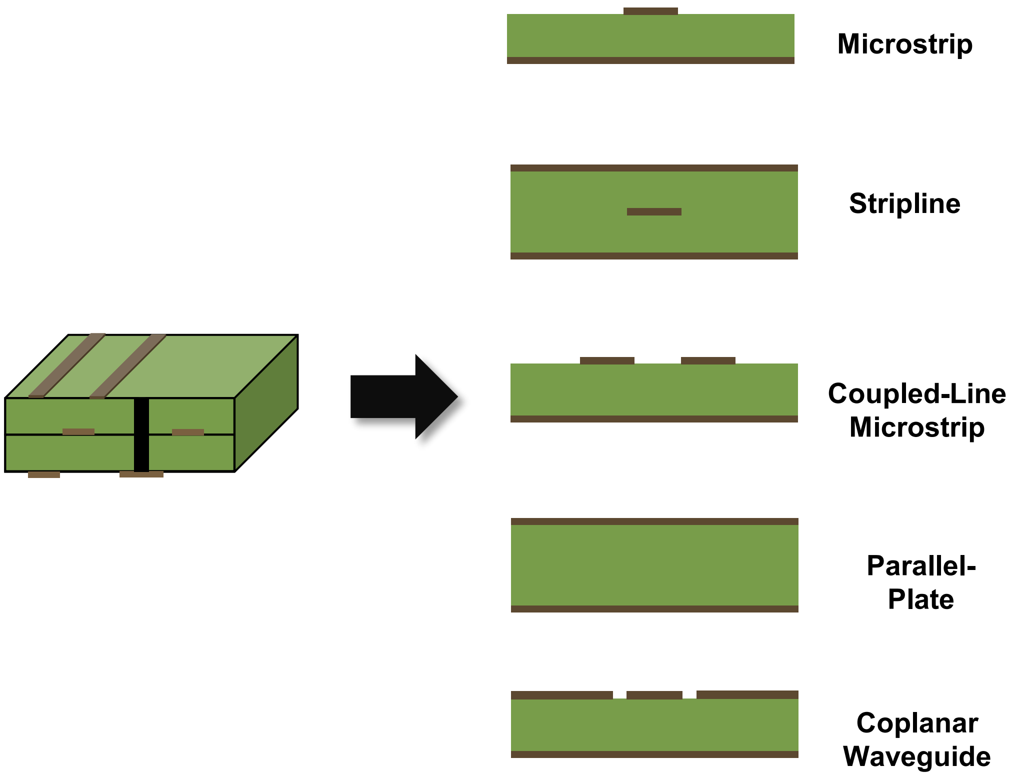
PDEs = Maxwell's Equations

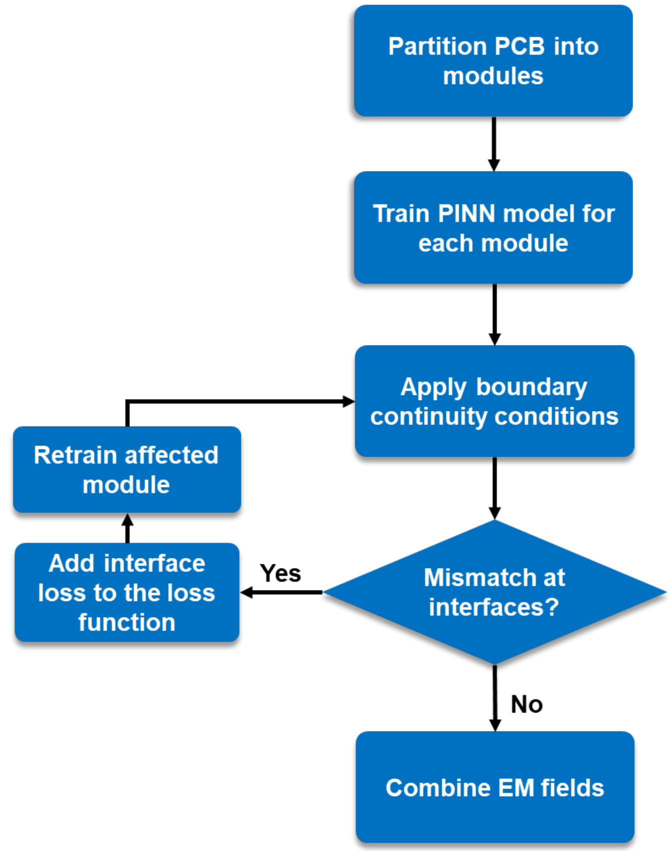
ML techniques are learning processes where real-scenario iterations will no longer be required if the problem has been learnt well.

EMI/EMC Simulations?

The Key Idea: PCB Modularization

EMC Forum

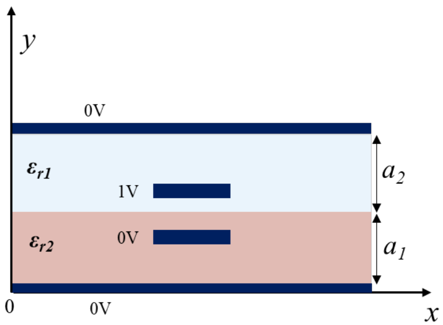


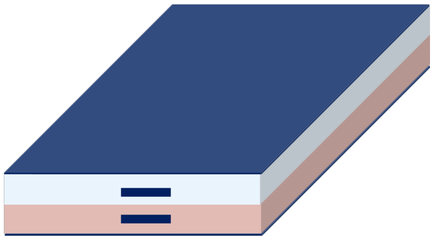


M. Kheir, K. Qian, M. Nabi and T. Ebel, "Modular Meshless Electromagnetic Simulation Using KAN-Based Physics-Informed Neural Networks," in *IEEE Journal on Multiscale and Multiphysics Computational Techniques*, vol. 10, pp. 452-458, 2025, doi: 10.1109/JMMCT.2025.3618590

Proposed AI Solver: KAN-PINN method

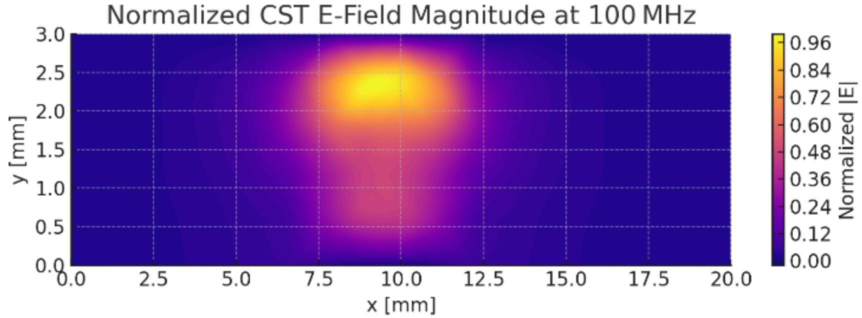
A 4-Layer PCB *E*-Field Results

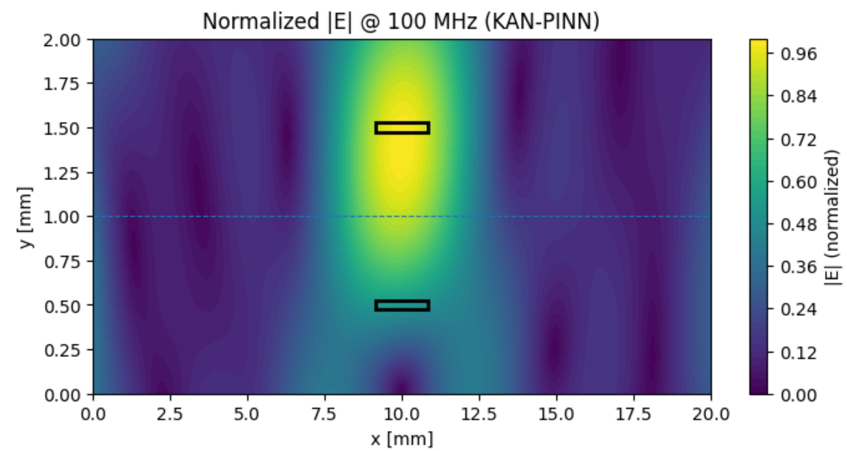




$$\nabla^2 u(x,y) + k^2 \varepsilon_r(y) u(x,y) = 0$$

Helmholtz Solution





M. Kheir, K. Qian, M. Nabi and T. Ebel, "Modular Meshless Electromagnetic Simulation Using KAN-Based Physics-Informed Neural Networks," in *IEEE Journal on Multiscale and Multiphysics Computational Techniques*, vol. 10, pp. 452-458, 2025, doi: 10.1109/JMMCT.2025.3618590

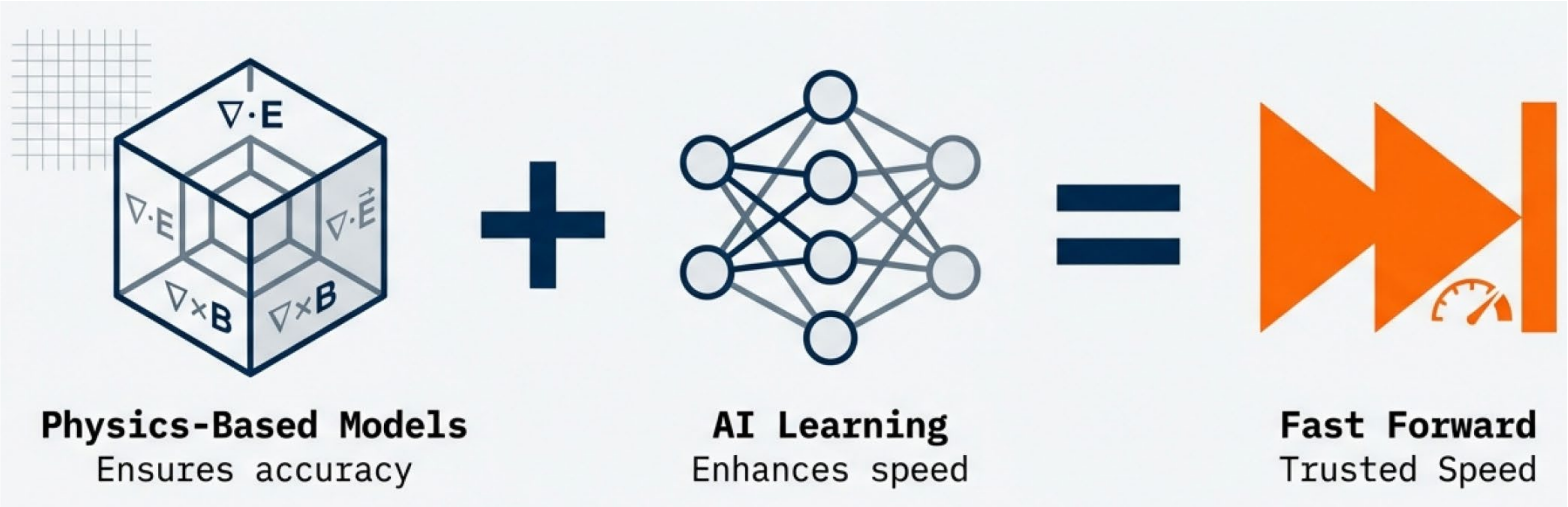
KAN-PINN vs. Commercial Solvers

EMC Forum

Metric	KAN-PINN	CST
Solver Type	Meshless PINN	Numerical (Finite-Integration)
Equation Solved	Helmholtz Wave Equation	Maxwell's Equations
ε_r Handling	Spatially Varying	Hexahedral mesh
Grid/Mesh	200×120 grid points (meshless)	6,851 mesh cells
Simulation Time	**36 sec**	**113 sec**

A tangible PCB check speed of 3x faster than a standard commercial full-wave solver.

Physics + AI = Speed and Credibility



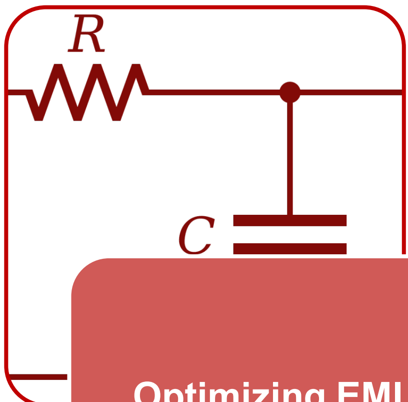
Why the KAN-PINN Solver Wins?

- It uses physics-based models enhanced by data-driven learning
- It works with limited simulation data (cost-efficient)
- Modular approach: it reuses learned building blocks across designs
- Designed for fast iterations

Other Potential PIML Directions for EMI

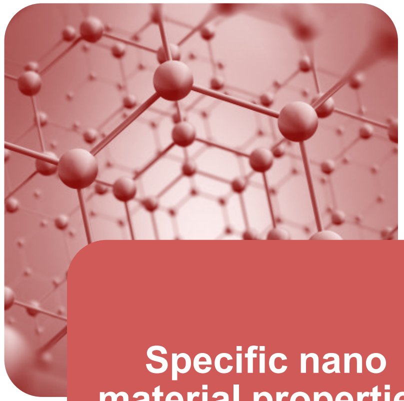
EMC Forum

EMI Filters



Optimizing EMI filter insertion loss function for better EMI response.

Shielding Materials



Specific nano material properties can be optimized to enhance a desired functionality.

Ferrites

Modeling and optimizing the magnetic properties of ferrite materials to achieve desired characteristics.

Conclusions

- There is a clear potential for employing PIML in simulating specific EMI/EMC problems which will open new horizons for new green simulation workflows.

- There are still, however, open research points and research challenges that are currently being addressed and investigated.

- The results from both MLP- as well as KAN-based PINNs have been demonstrated where the KAN-based PINNs can achieve the same results as MLP-based PINN, but with much fewer neurons.

- KAN-based PIML consequently reduce the training time required and introduce an energy-efficient and faster and more accurate training compared to MLP-based.

- PIML techniques have a wide range of applications for the EMI/EMC domains.

Stay tuned ☺