# Physics-Informed Deep Operator Network for 3-D Time-Domain Electromagnetic Modeling

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***Abstract*—In this project, we develop a physics-informed deep operator network (PI-DON) for solving realistic 3-D electromagnetic problems. The training process of PI-DON is unsupervised, eliminating the need to generate ground-truth data and thereby improving efficiency compared to traditional deep neural networks. As an electromagnetic solver, PI-DON demonstrates competitive efficiency compared to finite-difference time-domain (FDTD) for a single run, even when accounting for training time. After training, PI-DON demonstrates strong generalizability, enabling accurate and efficient modeling of cases with geometric and material variations, making it well-suited for uncertainty analysis and design optimization. We show the high accuracy, efficiency, and robust generalizability of the PI-DON solver through the modeling and uncertainty analysis of realistic 3-D electromagnetic problems.**

***Index Terms*—Computational electromagnetics, electromagnetic fields, machine learning, physics-informed neural networks.**

## I. Motivation

PHYSICS-informed neural networks (PINNs) have emerged as a promising approach in computational physics. Despite the popularity and theoretical effectiveness of PINNs, they suffer from significant challenges, including poor training efficiency, unknown generalizability, and difficulties in scaling to larger domains, which limit their applications to real-world problems. To address these limitations, Deep Operator Networks (DeepONets) offer a more flexible framework by learning nonlinear operators that map input functions to output functions. Unlike PINNs, which solve individual instances, DeepONets generalize across a family of problems. Their operator-based formulation and decoupling of training from geometry-specific constraints improve scalability and adaptability, making them well-suited for complex electromagnetic simulations. Thus, combining the physics-informed structure of PINNs with the operator-learning capabilities of DeepONets presents a promising direction for solving electromagnetic problems more efficiently and robustly.

## II. Proposed Method

We develop a Physics-Informed Deep Operator Network (PI-DON) for solving Maxwell's equations in the time domain, with a focus on realistic 3D electromagnetic problems. The workflow of the proposed PI-DON is illustrated in Fig. 1. The core of this approach involves training a neural operator—termed the Deep Curl Operator (DCO)—to approximate the spatial curl operator, using a modified 3D U-net architecture. This U-Net architecture incorporates 3D convolutional filters to process three-dimensional inputs and includes an additional down-sampling path, resulting in two separate encoding routes: one for input fields and another for spatial coordinates. This design enables the network to operate as a neural operator.

Then, the DCO is embedded within a physics-informed framework to construct the PI-DON solver. In this stage, the curl operator in Maxwell's equations is approximated by the DCO, while the time derivative of the electromagnetic fields is computed using a centered finite-difference method. To ensure accuracy in time-domain simulations for a given problem, the DCO is further trained using a physics-informed loss function derived from standard FDTD update equations. Material properties, boundary conditions, and sources are incorporated during this process.

The PI-DON framework offers several key advantages over traditional physics-informed machine learning approaches. First, by learning the curl operator rather than the full field solution, it reduces training complexity and computational cost. Second, due to the fully convolutional architecture of the DCO, PI-DON can handle input fields of arbitrary spatial dimensions, enabling flexible application to different computational domains. Third, once trained, PI-DON demonstrates strong generalizability across similar problem instances, making it especially effective for tasks involving repetitive simulations. We apply the PI-DON to simulate various electromagnetic problems and demonstrate its accuracy and efficiency in uncertainty analysis. This work highlights the application of physics-informed machine learning for practical electromagnetic modeling. A journal paper based on this study has been accepted by IEEE Transactions on Microwave Theory and Techniques [1].

## III. Numerical Results

Numerical experiments were conducted to evaluate the effectiveness of PI-DON across a range of practical problems. The PI-DON was first applied to simulate the well-known benchmark microwave structures of [2], including a microstrip low-pass filter and a microstrip branch-line coupler. Then, the PI-DON was used to simulate an SRR/strip wire unit cell, following the geometry described in [3]. Unlike data-driven models, PI-DON was trained in an unsupervised manner, eliminating the need for ground-truth data and significantly reducing training overhead. Even when accounting for training

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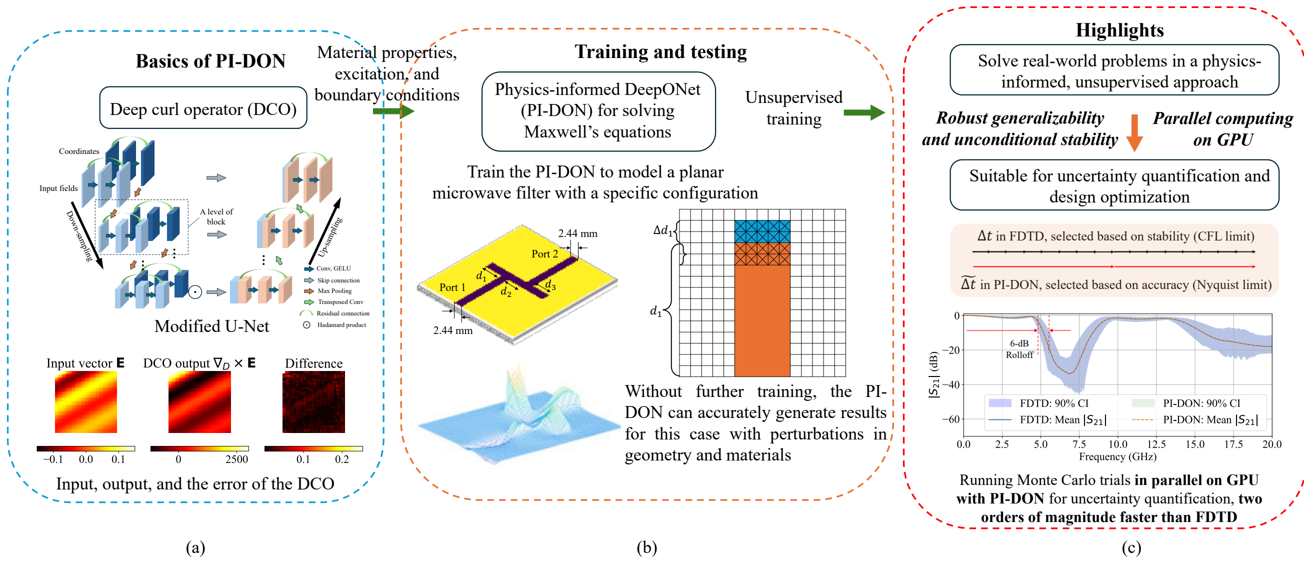


Fig. 1. Workflow of the Physics-Informed Deep Operator Network (PI-DON) for solving Maxwell's equations. (a) A modified 3D U-Net is trained to approximate the curl operator, forming the Deep Curl Operator (DCO). (b) The DCO is embedded in the PI-DON framework to solve Maxwell's equations with incorporated material properties, boundary conditions, and source terms. Once trained, the PI-DON generalizes well to variations in geometry and materials, making it suitable for uncertainty analysis. (c) Key features of PI-DON: unconditional stability, strong generalizability, and efficient parallel execution on GPUs. The right panel also shows the mean $|S_{21}|$ and 90% confidence interval for the planar microstrip filter shown in (b), computed using PI-DON across Monte Carlo trials.

TABLE I
EXECUTION TIME COMPARISON BETWEEN FDTD AND PI-DON FOR MONTE CARLO EXPERIMENTS AND ACCURACY OF PI-DON

| Geometry | MC FDTD (hours) | MC PI-DON (hours) | MRE of PI-DON |
|---|---|---|---|
| Filter | 32.50 | 0.23 | $4.6 \times 10^{-3}$ |
| Coupler | 32.19 | 0.18 | $3.2 \times 10^{-3}$ |
| SRR | 153 | 1.05 | $2.8 \times 10^{-3}$ |

time, the execution time of PI-DON was comparable to or shorter than that of FDTD. Across all test cases, the trained PI-DON had a mean relative error (MRE) on the order of $10^{-3}$.

Once trained on a specific case, PI-DON can accurately solve a range of similar problems without retraining. Additionally, its time step is not constrained by the Courant–Friedrichs–Lewy (CFL) condition. Instead, the time step can be set based on accuracy, further improving the computational efficiency. Moreover, the PI-DON can be run in parallel on GPUs. These features make PI-DON well-suited for tasks requiring repetitive simulations, such as uncertainty analysis and design optimization. In this study, the trained PI-DON models were used to conduct large-scale uncertainty analysis via Monte Carlo (MC) simulations. For each case, over 1000 MC trials were performed with varying geometric and material parameters. PI-DON demonstrated significant computational efficiency in Monte Carlo (MC) simulations. Table I compares the execution time and corresponding MRE between PI-DON and FDTD across different cases. The results show that PI-DON provides over 100× speedup compared to FDTD, without sacrificing accuracy.

## IV. FUTURE DIRECTIONS AND IMS EXPERIENCE

The MTT-S Graduate Fellowship has played an important role in shaping my career goals. It provided both recognition and resources that encouraged me to deepen my expertise in scientific machine learning and numerical modeling. The support from this program has reinforced my confidence in continuing on this interdisciplinary path. Looking ahead, I plan to pursue a career that focuses on numerical methods and machine learning, whether in academia or industry. I am particularly interested in roles that involve the development or application of computational techniques to solve real-world electromagnetic or multi-physics problems.

Attending IMS 2024 was a valuable and eye-opening experience. I was especially impressed by the scale and breadth of the industry exhibition, which highlighted the close connection between academic research and commercial innovation. It was also a great opportunity to engage with leading researchers and industry experts, exchange ideas, and explore emerging trends in the field of microwave engineering. This experience has further motivated me to contribute to impactful research and practical solutions in this area.

## REFERENCES


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