

Data-efficient and Ultra-fast Surrogate Models for Simulating Nanophotonic Power-splitters

Aggraj Gupta⁽¹⁾, Uday K Khankhoje⁽¹⁾, and Constantine Sideris⁽²⁾

⁽¹⁾ Electrical Engineering, Indian Institute of Technology Madras, Chennai, India

⁽²⁾ Electrical and Computer Engineering, University of Southern California, Los Angeles, USA

Abstract—In this paper we explore neural-network based surrogate models for simulating the response of nanophotonic power splitters with arbitrary split ratios. In particular we investigate the hypothesis that using internal fields as an intermediate variable helps reduce the data requirements for network training. We deploy the recently proposed U-Net and Fourier Neural Operator (FNO) approaches to learn the relation between a pixel-based input device geometry and the intermediate fields and cascade them with another neural network to arrive at the modal transmittance. We compare our finding against naive approaches that directly learn the relation between the input device geometry and transmittance, and find a six fold reduction in the training root mean square error value. This research opens the route to faster and more data efficient approaches to inverse design of nanophotonic devices.

I. INTRODUCTION

To handle the complexity of designing nanophotonic integrated circuits, automated tools are becoming critical [1]. These tools significantly speed up the design process. Simulation accuracy and computational time are the tradeoffs that need to be navigated in the design process.

As devices become more sophisticated, full-wave simulations, accurate as they are, become slow. Recent studies [2], [3] used 3D finite difference time domain (FDTD) solvers for the optimization of optical splitters, however, they took 72 and 120 hours, respectively, to achieve desired designs. Thus, designing devices with specific performance metrics is a growing research area that requires fast and accurate solvers.

We propose data-efficient, fast and accurate surrogate models based on deep-learning to simulate the performance of a given device, with the goal of replacing conventional fullwave solvers. We use information from intermediate variables, such as fields in the domain, to understand the relationship between design and the device's modal transmittance response. This ultra-fast solver can further aid in optimizing nanophotonic devices. We present quantitative results that compare the accuracy of the solver against conventional methods that learn the modal transmittance directly from the device design.

II. METHODS

We generated the dataset using a commercial FDTD solver (Lumerical) to train our forward surrogate model. In a proof-of-concept test, we applied our methodology to simulate a 1×2 nanophotonics splitter using the 2D FDTD numerical method. We excite the fundamental TE mode at a single mode input waveguide with the mode source that injects a user-defined guided mode into the input waveguide. We then simulate the

modal transmittance at both output ports at a randomly chosen wavelength in the range $1.4 - 1.6 \mu\text{m}$. The simulation region is divided into 64×64 pixels. The input, $x \in \mathbb{R}^{64^2}$, contains the permittivity of the pixel, which can either be silicon or air. An element in the training set is generated by choosing x at random, and simulating its modal transmittance at a chosen wavelength. We also store the field information in the simulation domain as part of the training-set entry. Fig. 1 shows an instance of the permittivity distribution of a sample nanophotonic splitter, and the corresponding absolute value of the magnetic field, H_z , in the domain at the end of a 2D FDTD simulation. Each end of the input and output waveguides of the splitters are terminated by perfectly matched layers (PML) to truncate the computational region.

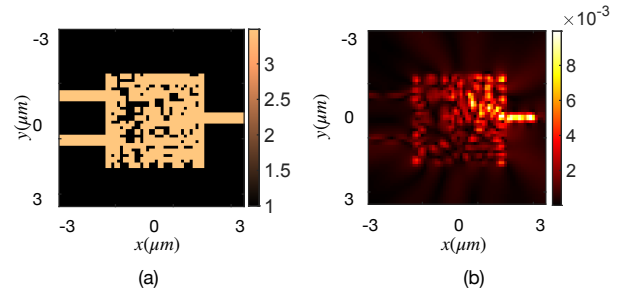


Fig. 1. (a) Sample 1×2 power splitter of size $2.6 \times 2.6 \mu\text{m}^2$ tessellated into 64×64 pixels, with waveguide widths equal to 250 nm, and (b) Field distribution in the simulation domain.

Our surrogate model employs a cascade of two neural networks:

- 1) The first network learns the relation between the permittivity distribution and the absolute value of the magnetic field. We explore two options for this learning: (i) a neural operator learning architecture, specifically the Fourier Neural Operator (FNO) [4], or (ii) a convolutional neural network originally developed for biomedical image segmentation, the U-Net [5].
- 2) The second network learns the relationship between the absolute value of the fields and the modal transmittance at the power splitter's output port. We determine the power transmitted in a mode using a calculation called the mode overlap integral. This calculation informs us about the amount of power that can move in the intended mode from a specific input field.

The cost function used to train FNO and CNN is: $\frac{1}{n} \sum_{i=1}^n \|y - y'\| / \|y\|$ and $\frac{1}{n} \sum_{i=1}^n \|(T_i - T'_i)\|$, respectively. Here, y and y' are the true and predicted value of magnetic field, respectively, and T_i and T'_i are the true and predicted values of the modal transmittance at a chosen wavelength.

III. NUMERICAL RESULTS

We train the neural networks and show the evolution of the test rmse with dataset size for direct learning as well as intermediate-variable based learning (Fig. 2(a)). As can be seen, the approaches based on intermediate field variables perform significantly better than using a direct approach, featuring 6 times lower rmse at the maximum dataset size.

Next, in Fig. 2(b), we show results for the accuracy in predicting the modal transmittance from the approaches under consideration. As can be seen, the intermediate fields approach gives significantly more accurate results than a direct approach. For instance, in the direct approach, approximately 30% of the samples have error less than 1 % in transmittance, whereas this number is 65% in the intermediate-variable case. The corresponding field predictions for the FNO and U-Net approaches are shown in Fig. 3, from where it can be inferred that both networks are able to predict the fields in the domain precisely. In Fig. 4, a scatter plot compares predicted modal transmittances for both splitter output ports. Using a dataset of 18k, our proposed method requires much less data than the direct approach. We conjecture that this is because although the relation between the input geometry and modal transmittance is highly nonlinear, having the interior fields as an intermediate variable helps ease this nonlinearity.

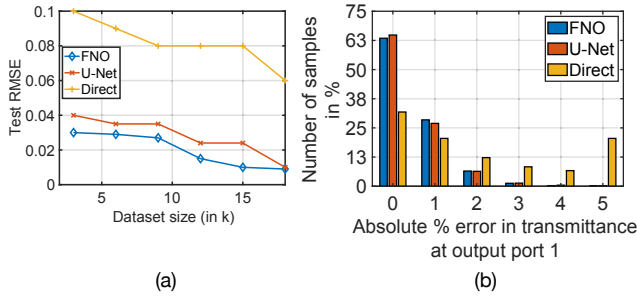


Fig. 2. (a) Comparison of the test rmse plot for the three approaches for the surrogate models to simulate nanophotonic splitters, (b) Histogram plot for comparing the test error between different surrogate models at output port 1

IV. CONCLUSION

In this paper, we show that using fields as an intermediate step in the learning approach helps drastically reduce the dataset size required for neural network training. The FNO is preferred over U-Net since the FNO learns the neural operator and its architecture is independent of the input size.

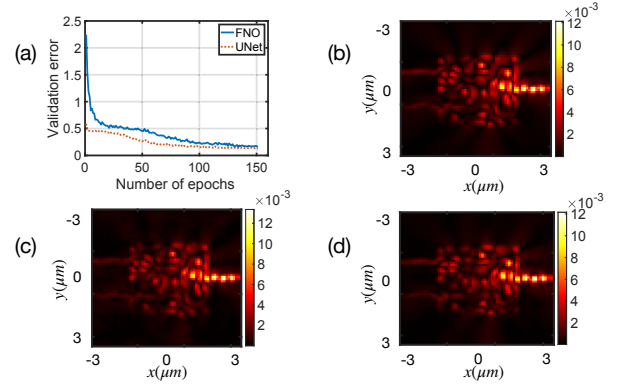


Fig. 3. (a) Comparison of the validation error curves for FNO and U-Net networks, fields in the simulation domain: (b) true, (c) using FNO, and (d) using U-Net.

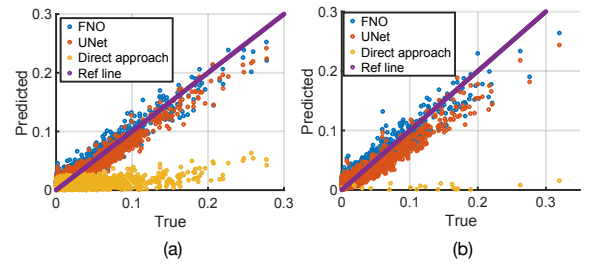


Fig. 4. Comparison of modal transmittance using the proposed approach and the direct approach at: (a) port 1, and (b) port 2.

While the results are promising, more research is required to further reduce the modal transmittance error since it is critical for incorporating surrogate models into inverse design methodologies [6], which is the eventual goal of this work.

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