

# Photonics Inverse Design Over Localized Spectral and Spatial Regions

Nasim Mohammadi Estakhri

*Fowler School of Engineering, Chapman University, Orange, CA 92866 USA  
Schmid College of Science and Technology, Chapman University, Orange, CA 92866 USA*

\* estakhri@chapman.edu

**Abstract**—Using a region-specified residual convolutional neural network, we design a variety of nanostructures with desired scattering and absorption responses. This technique allows for single-shot training over different wavelengths of interest and is especially suitable for realizing narrowband responses and/or localized tuning of the response. In this context, we will discuss the impact of the quality of the training dataset on the accuracy of the results over different wavelength regions.

**Keywords**—*photonics inverse design, residual convolutional neural networks, scattering, absorption, nanostructures, nanoparticles.*

## I. BACKGROUND

Unlike traditional optimization techniques such as genetic algorithms or particle swarm optimization [1]-[4], machine learning is a data-driven approach, and the size and quality of the training dataset are important factors in the performance of the network [5]. In electromagnetic problems, this dataset is typically generated through full-wave simulation of three-dimensional structures, which is a computationally expensive task. In some cases, analytical or semi-analytical solutions are available, which can partially eliminate the computation costs associated with the process of generating the dataset. Given the scarcity of such analytical solutions, in this work, we aim to study the impact of the quality of the dataset on the accuracy of the inverse design, using a rather small training dataset (less than 2000 samples) and through the inverse design of nanostructures with varying absorption and scattering cross sections. In particular, and by using a region-specified training approach [6], we study the accuracy of such inverse design over different wavelength regions with different data qualities.

## II. RESULTS AND DISCUSSIONS

Multilayered nanoparticles have been extensively studied in the context of engineering their extinction properties [7]. Here, we use a residual convolutional neural network (CNN) to model the scattering and absorption response of a three-layer subwavelength nanoparticle (silicon dioxide/silver/silicon dioxide). The particle is characterized by three parameters (radius of each layer) and the network is trained on the combined absorption/scattering spectrum of the particles to generate these three parameters. In this regard, the inputs of the residual CNN are two metrics where the first metric is the normalized absorption cross-section of the particle, and the second metric is the ratio between the absorption and scattering cross-sections of the particle. Both metrics are calculated over the wavelength range of 350-700 nm for 2310 particles and by using Mie theory. Out of these particles, we remove those that exhibit extremely high values in metric two [6], remaining with 1452 particles. Given that the training data is over a wide range of wavelengths, the scattering/absorption is highly varying over this range. In particular, the response is richer and exhibits several resonant peaks close to 350 nm while it is flat and featureless near 700 nm. To capture all these behaviors in a single-shot training and with a small training dataset of ~1500 particles, we use the same data points multiple times with various spectral filters. The spectral filters are placed at different wavelengths and have different random widths. This allows us to increase the training dataset 25 folds and train the model on localized spectral regions. Fig. 1a shows the training convergence of the model. Fig. 1b shows the inverse design performance of the network. In each panel, the desired metrics are shown with solid lines and the outcome of the network is shown with dashed lines. As it can be seen, using a very small dataset, the network successfully predicts particles with the desired absorption and scattering in localized wavelength regions near 350 nm. However, as the wavelength increases (i.e., the quality of the training data decreases and it is quite featureless), as expected there are no suitable particles available. Using the spectral filters, these two ranges are successfully decoupled on the training. In our presentation, we will discuss more results related to localized spectral and spatial inverse design.

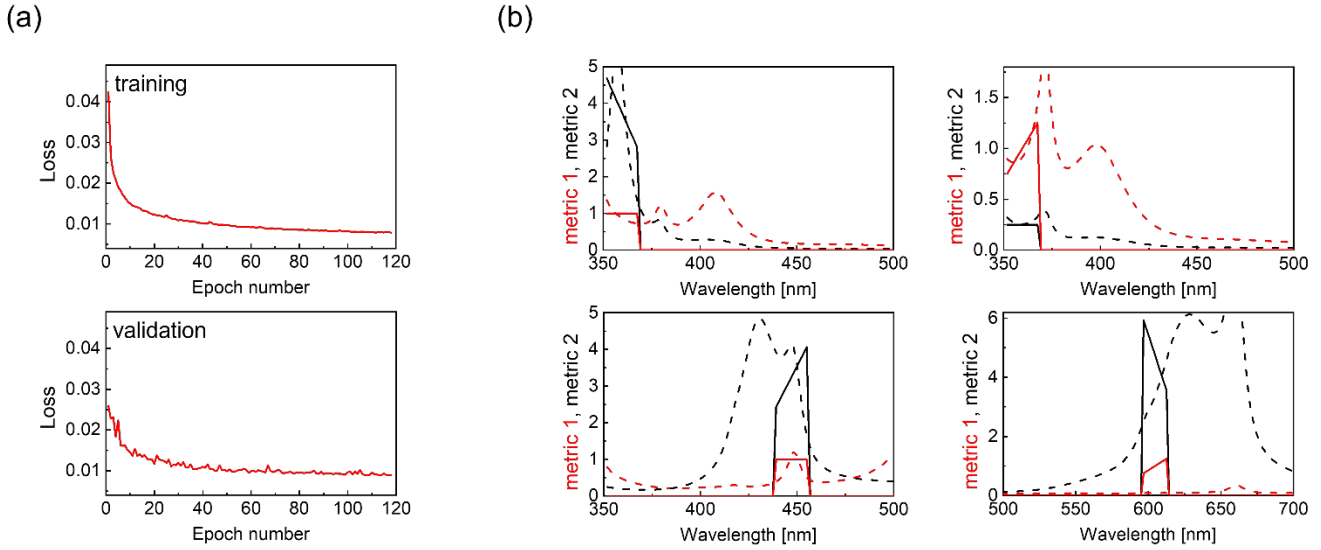


Fig. 1. (a) Training and validation convergence of the model. (b) Performance of the network over different wavelength ranges [6].

#### REFERENCES

- [1] D. S. Weile and E. Michielssen, "Genetic algorithm optimization applied to electromagnetics: A review," *IEEE Transactions on Antennas and Propagation* 45, no. 3 (1997): 343-353.
- [2] J. Robinson and Y. Rahmat-Samii, "Particle swarm optimization in electromagnetics," *IEEE transactions on antennas and propagation* 52, no. 2 (2004): 397-407.
- [3] A. Didari, N. M. Estakhri, and N. Mohammadi Estakhri, "Adaptive plasmonic metasurfaces for radiative cooling and passive thermoregulation," *Frontiers in Photonics* 4 (2023): 1193479.
- [4] A. Mayer, H. Bi, S. Griesse-Nascimento, B. Hackens, J. Loicq, E. Mazur, O. Deparis, and M. Lobet, "Genetic-algorithm-aided ultra-broadband perfect absorbers using plasmonic metamaterials," *Optics Express* 30, no. 2 (2022): 1167-1181.
- [5] V. Gudivada, A. Apon, and J. Ding, "Data quality considerations for big data and machine learning: Going beyond data cleaning and transformations," *International Journal on Advances in Software* 10, no. 1 (2017): 1-20.
- [6] A. Vallone, N. M. Estakhri, and N. Mohammadi Estakhri, "Region-specified inverse design of absorption and scattering in nanoparticles by using machine learning," *Journal of Physics: Photonics* 5, no. 2 (2023): 024002.
- [7] W. Liu, A. E. Miroshnichenko, D. N. Neshev, and Y. S. Kivshar, "Broadband unidirectional scattering by magneto-electric core-shell nanoparticles," *ACS nano* 6, no. 6 (2012): 5489-5497.