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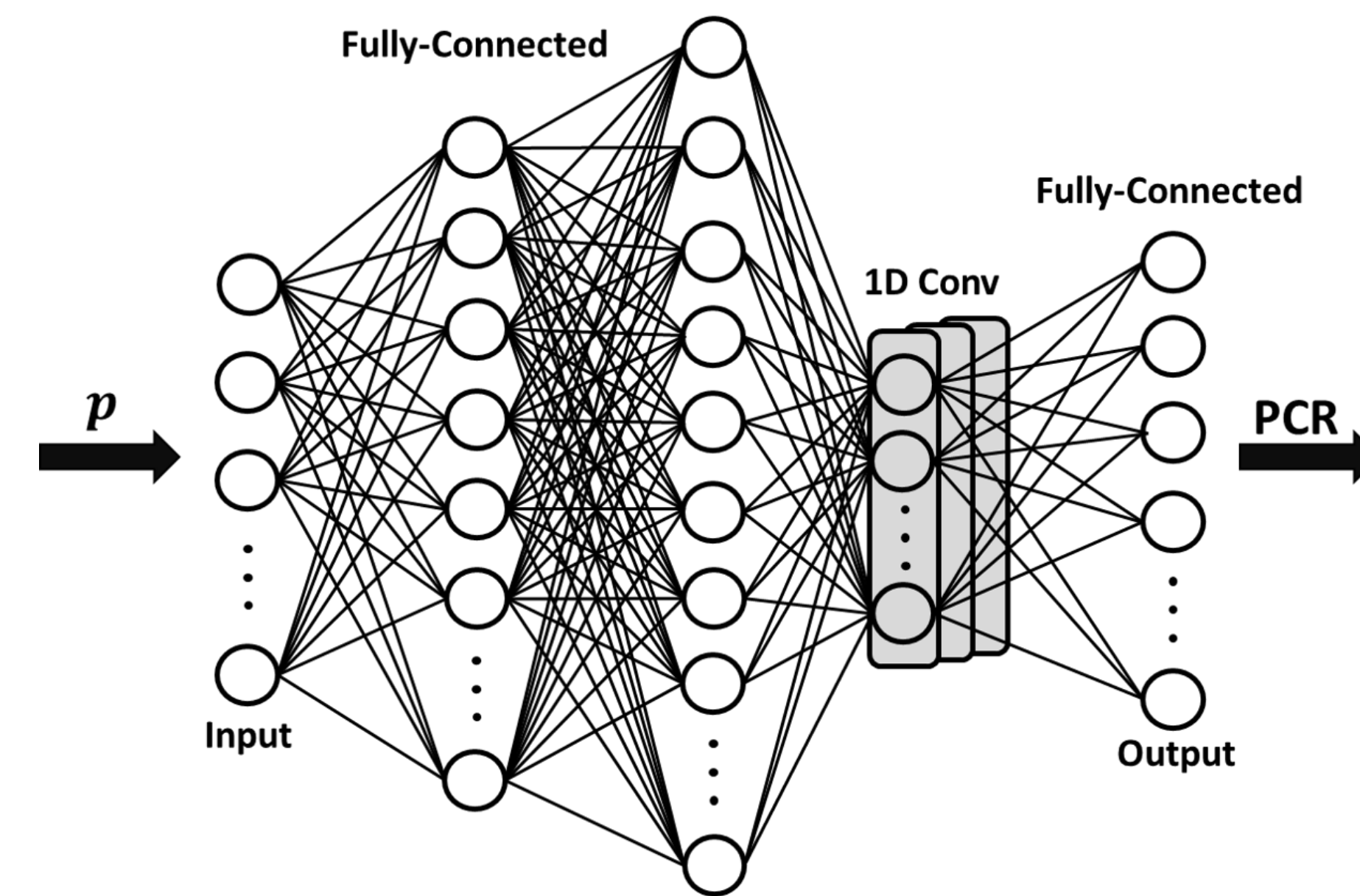
Member of GRK 2642: Towards Graduate Experts in Photonic Quantum Technologies

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**Deep learning
enhanced
optimization of a
broadband and
wide-angle
reflective linear
terahertz
polarization
converter**

Abstract

Artificial neural networks (ANNs) are known to be a versatile tool for device optimization. This work proposes a method to optimize a polarization converter composed of T-shaped periodic resonators, inclined at 45 deg using an ANN. The result is compared with previous work conducted using CST simulation, demonstrating broadband and wide-angle reflective linear polarization conversion. Employing an ANN resulted to improved performance metrics, leading to **increased fractional bandwidth of 7.6% for normal incident and 9.8% for 45° incident angle**. The neural network achieved a **mean square error (MSE) as low as 5.78×10^{-5}** , indicating high accuracy. This approach demonstrates the efficiency of ANNs in designing metasurfaces for a wide range of applications.

ANNs for inverse design

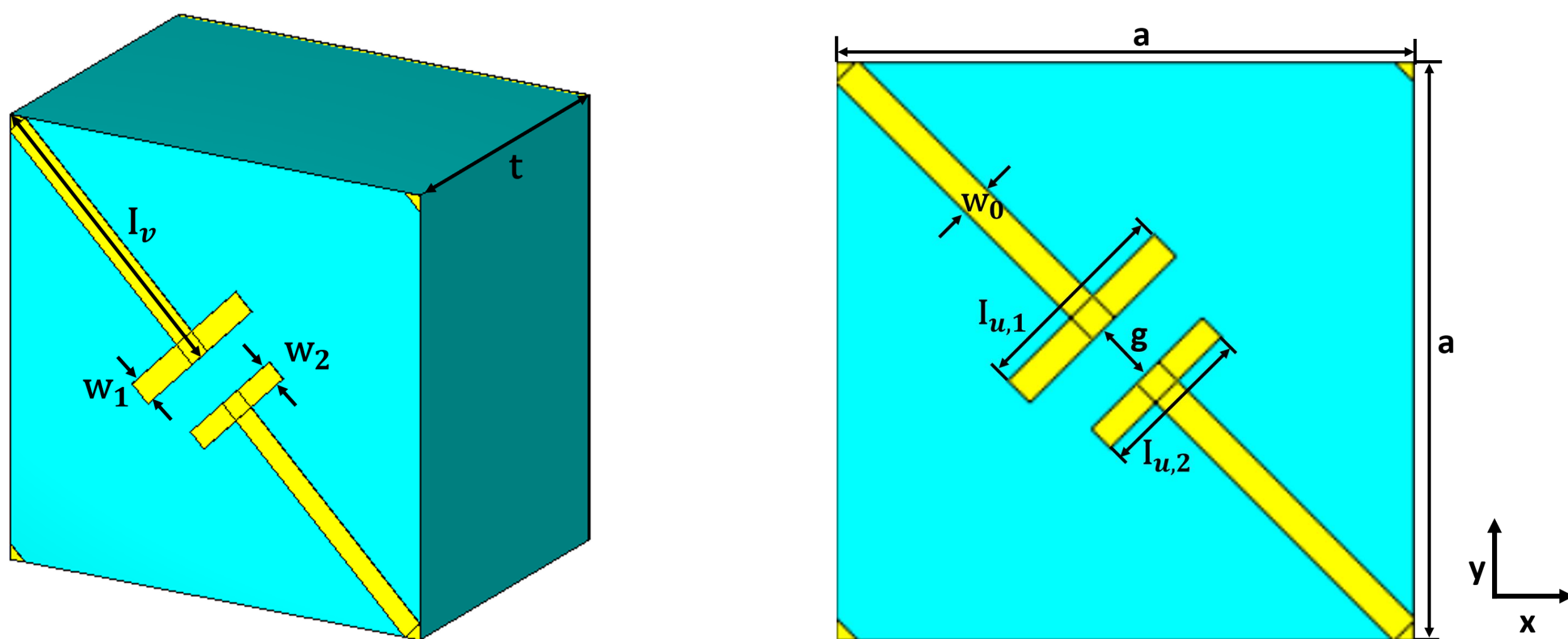


Schematic representation of the ANN structure.

The **nine-dimensional input space** is processed by two fully connected layers, with **32 nodes** and **1024 nodes**, respectively. Followed by a **1D convolution layer** with **16 filters** and a **kernel size of 32**. Finally, there is a fully connected **output layer** with **1001 nodes**.

- Z-Score normalization: $\bar{p}_i^n = \frac{p_i^n - \mu_i}{\sigma_i}$
- ReLU activation for all but the output layer: $a(x) = \max(0, x)$
- Adam optimizer with a mini-batch size of 16.
- 25,450 samples in total, 20% for test and validation.

Linear Polarization Converter



Contains a gold reflection plate at the backside, a cyclic olefin copolymer (COC) dielectric layer, and a conducting T-shaped resonator structure.

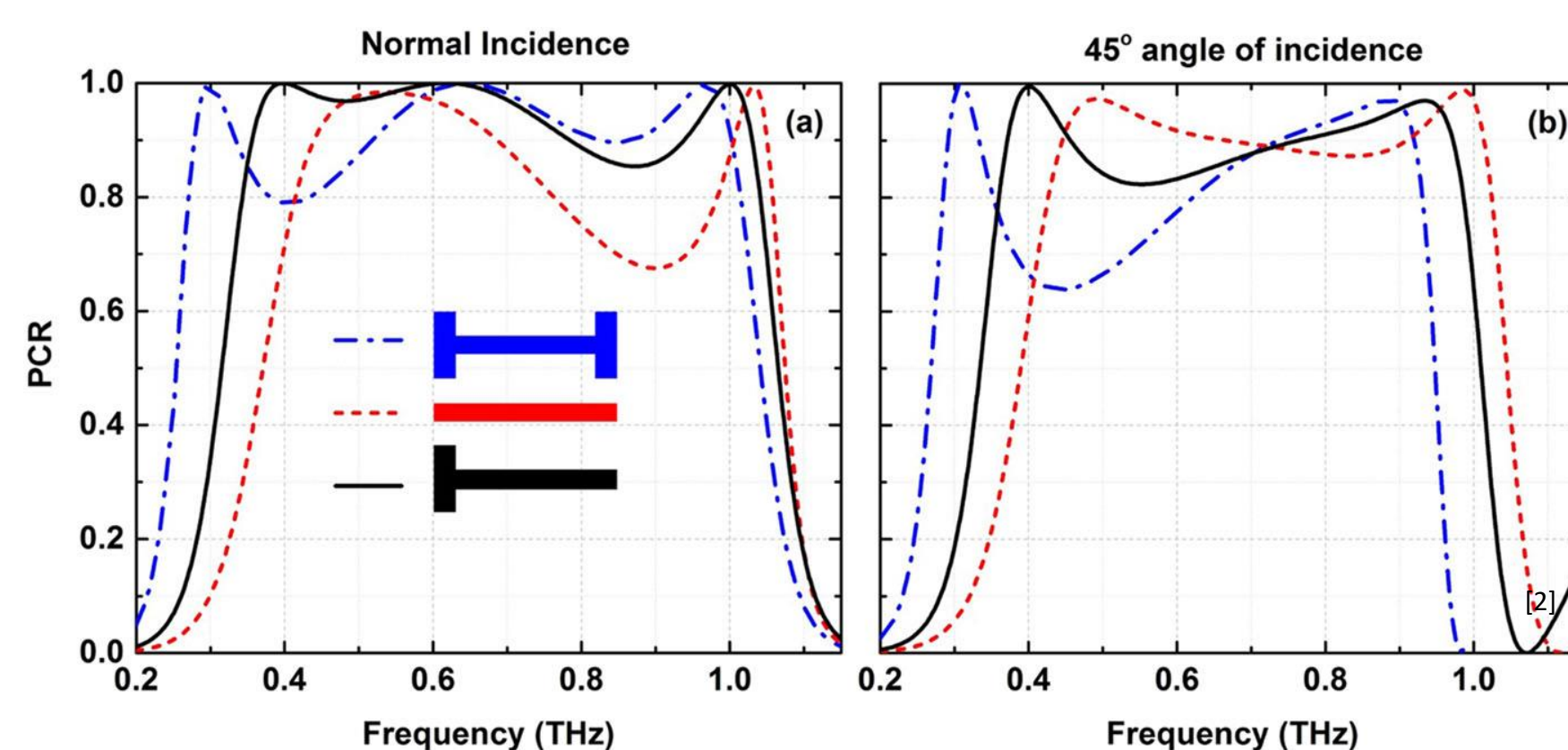
Design parameters:

$\mathbf{p} = (a, t, g, w_0, w_1, w_2, I_{u,1}, I_{u,2})$ serve as input for the neural network.

$$\text{PCR}(f) = \frac{|r_{xy}(f)|^2}{|r_{xy}(f)|^2 + |r_{yx}(f)|^2}$$

Polarization conversion ratio (PCR) used to evaluate the performance of the device.

Simulated PCR for different dipole resonator geometries at normal (a) and 45° (b) incidence.



Results

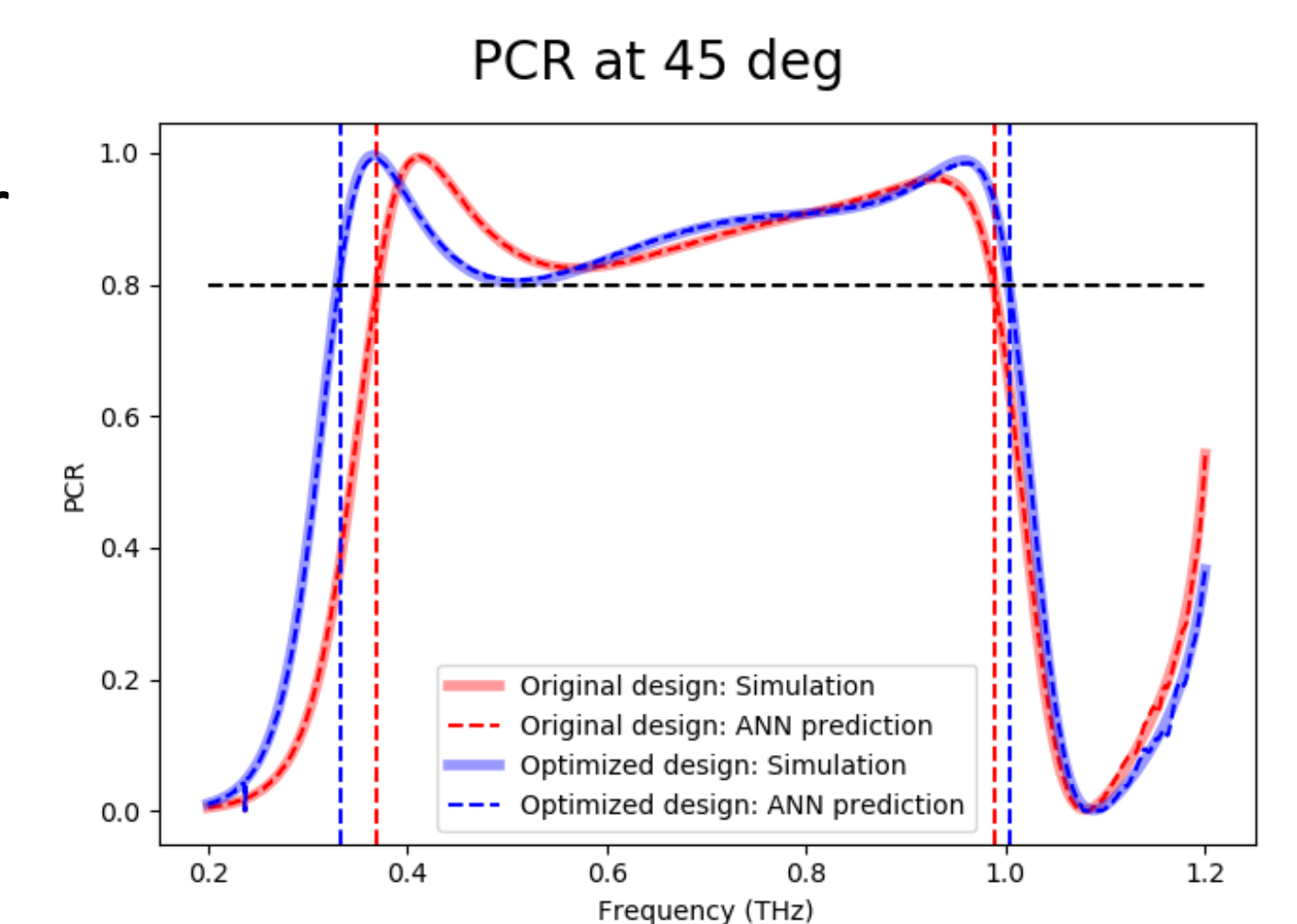
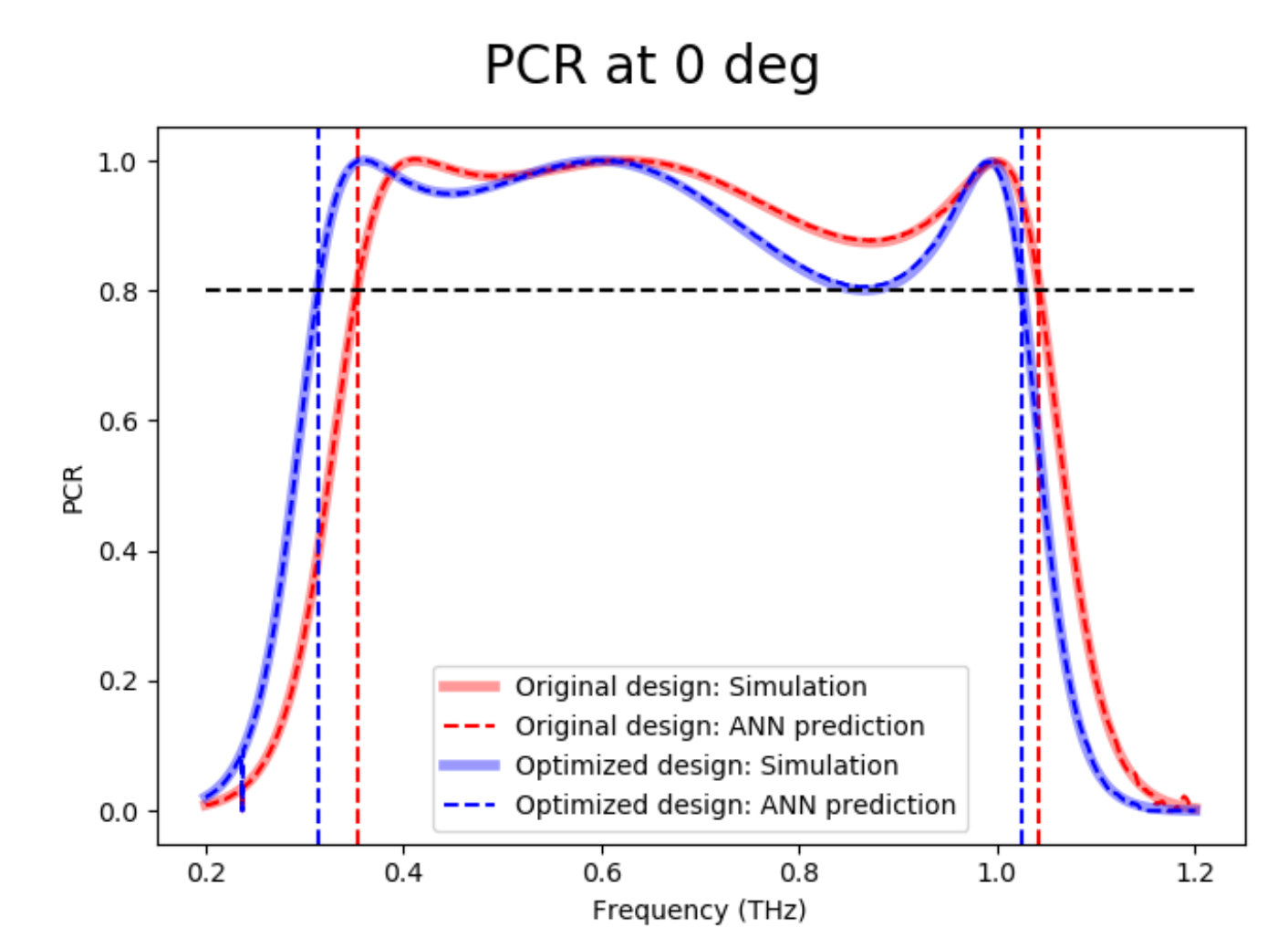
- 1,562,500 PCRs were predicted, using the ANN.
- Calculate the fractional bandwidth $B_\theta = 2 \frac{f_{2,\theta} - f_{1,\theta}}{f_{2,\theta} + f_{1,\theta}}$ where $\text{PCR} \geq 0.8$.
- Define the FOM as: $FOM = \sum_{\theta \in \{0^\circ, 45^\circ\}} B_\theta$
- Search the predictions for the best performing parameter set \mathbf{p}_{opt} .

Dataset size for training vs. MSE:

4600	1.50×10^{-3}
9200	2.62×10^{-4}
20,614	5.78×10^{-5}

- High accuracy in network predictions, even using a smaller set of training data.

- The fractional bandwidth could be increased by 7.6% for 0° incident and 9.8% for 45° incident angle.



Data collection:

Each component \mathbf{p}_i^n is uniformly distributed according to $\bar{\mathbf{p}}_i^n \sim \mathcal{U}_{[\mathbf{p}_{i,\min}, \mathbf{p}_{i,\max}]}$ within the range $\mathbf{p}_{i,\min} = 0.9 \mathbf{p}_{i,\text{init}}$, $\mathbf{p}_{i,\max} = 1.1 \mathbf{p}_{i,\text{init}}$. With $n \in \{1, 2, \dots, N\}$ where N is the total number of random design parameters.

Incident angle θ_i	Optimized design				Original design	
	ANN prediction		Simulation		Simulation	
	Frequency range in THz	Fractional bandwidth	Frequency range in THz	Fractional bandwidth	Frequency range in THz	Fractional bandwidth
0°	0.314 – 1.025	106.2	0.313 – 1.025	106.4	0.353 – 1.042	98.8
45°	0.332 – 1.004	100.6	0.329 – 1.002	101.1	0.369 – 0.989	91.3