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SAND2022-14067C

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Optimization of an Optical Shutter using Machine Learning

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Presented at: Society of Engineering Science Annual Technical Meeting

Texas A&M Engineering Experiment Station

October 16-19, 2022

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SAND #: X123456789

This material is based upon work supported by the
National Science Foundation under Grant No. 1922758

Acknowledgement. This work was supported by the Laboratory Directed Research and Development Program at Sandia National Laboratories. Sandia National Laboratories is a multimission laboratory managed and operated by National Technology and Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell International, Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA-0003525. This paper describes objective technical results and analysis. Any [illegible]partment of Energy or the United States Government.

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Topology Optimization

- Topology Optimization
  - Structural
  - Photonics
- Most basic form
  - Discretize problem
    - Governing equations, boundary conditions
    - Finite element setup
  - Allocate a given amount of material across the points
    - **Density function (rho)**
  - Determine objective (cost) function to minimize
    - Extinction ratio and temperature rise targets
  - **Solve finite element model**
  - Sensitivity analysis
  - Updates
  - **Repeat**

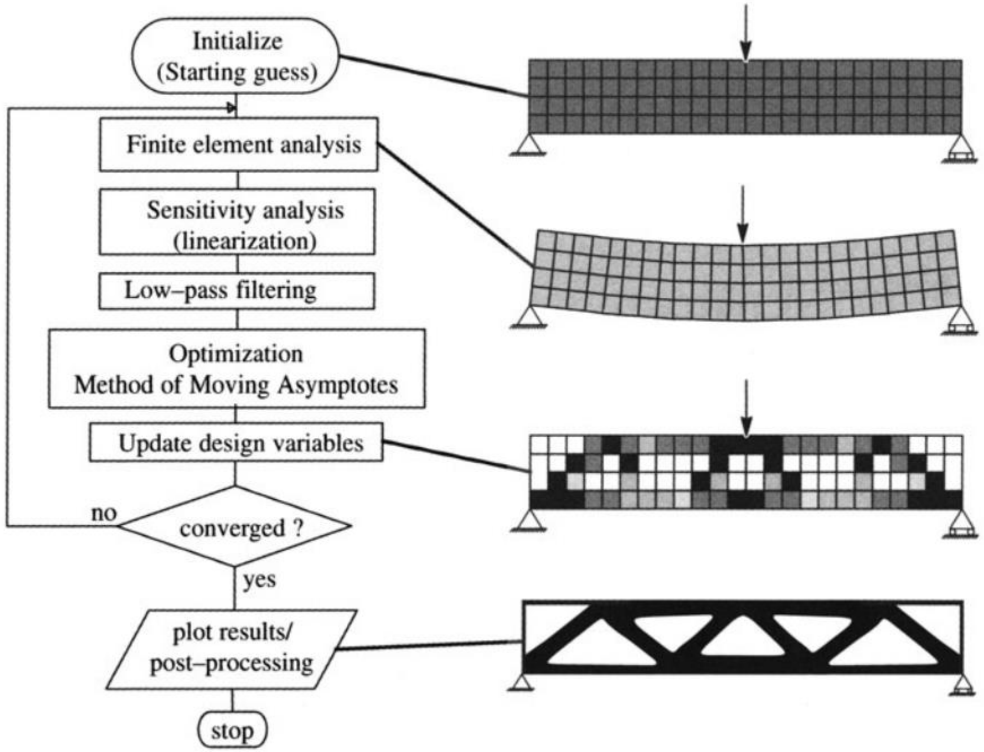
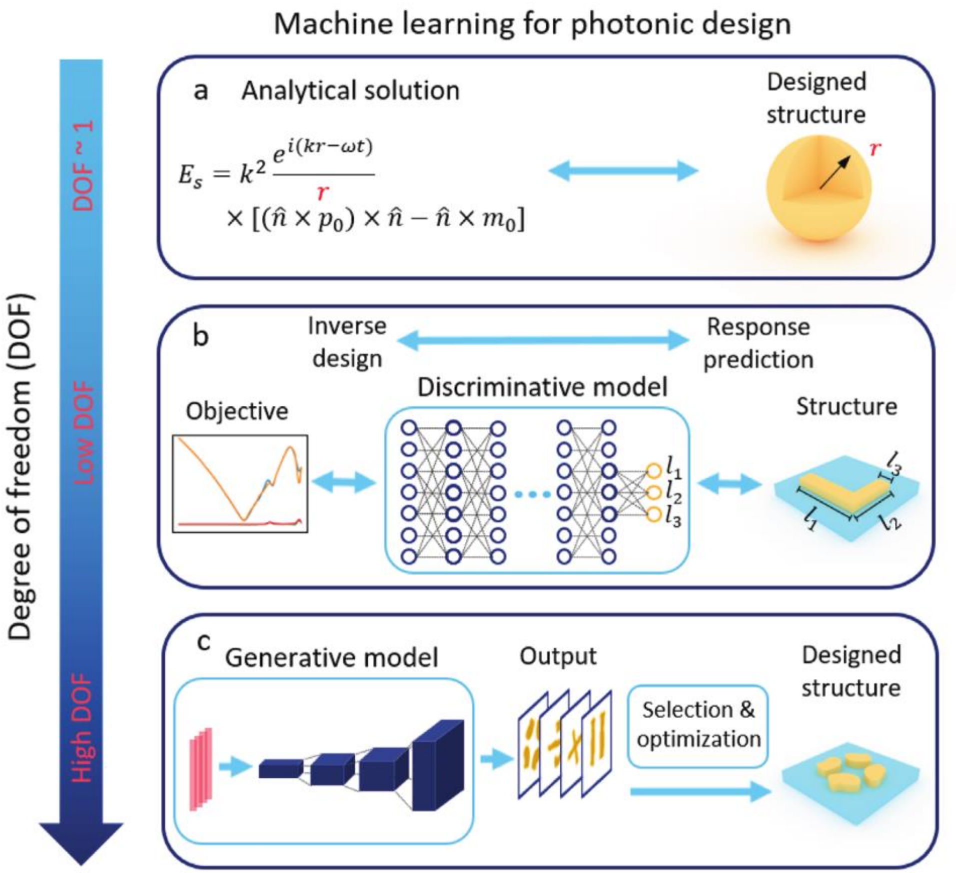


Fig. 1.5. The flow of computations for topology design using the material distribution method and the Method of Moving Asymptotes (MMA) for optimization. The low-pass filter step (filtering of sensitivities) is discussed in Sec. 1.3.1.

Source: Bendsoe and Sigmund, "Topology Optimization: Theory, Methods, and Applications", 2003

Motivation

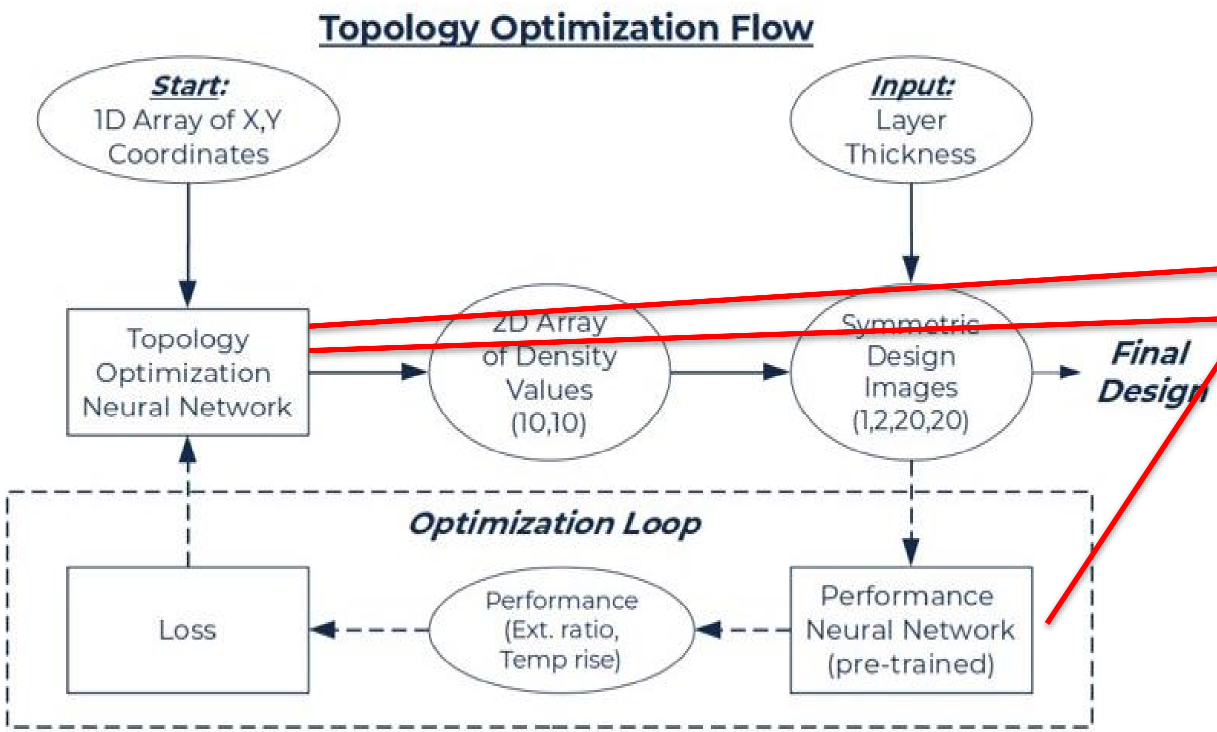
- Challenges
  - **Requires costly finite element solver calls each iteration**
  - Large optimization problems
    - Parallel Computing
    - Advanced iterative solvers
    - Multi-scale or Multi-Resolution Approaches
- Neural Networks in Topology Optimization [1]
  - Supplement
  - Replace
    - Solver
    - Predict density function [2]



Machine learning for photonic design [1]

[1]Z. Liu, D. Zhu, L. Raju, and W. Cai, “Tackling Photonic Inverse Design with Machine Learning”, Advanced Science, vol. 8, no. 5, p. 2 002 923, Mar. 2021.
[2] A. Chandrasekhar and K. Suresh, “TOuNN: Topology Optimization using Neural Networks”, Structural and Multidisciplinary Optimization, vol. 63, no. 3, pp. 1135–1149, Mar. 2021.

Neural Network Based Topology Optimization



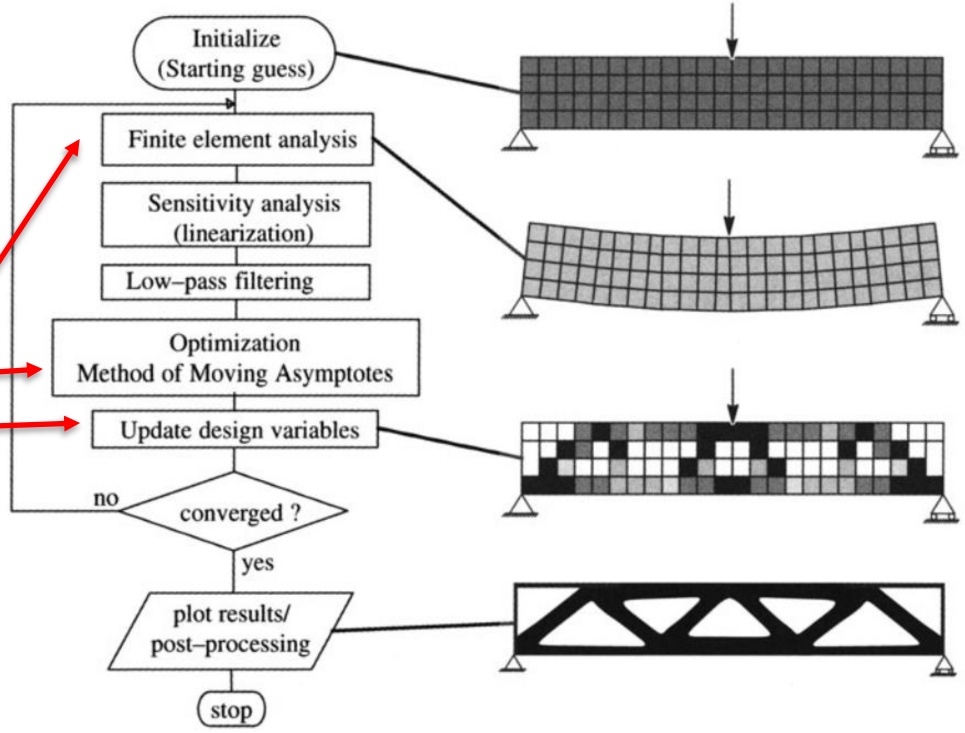


Fig. 1.5. The flow of computations for topology design using the material distribution method and the Method of Moving Asymptotes (MMA) for optimization. The low-pass filter step (filtering of sensitivities) is discussed in Sec. 1.3.1.

Can we perform traditional topology optimization with a dual neural network approach?

Optimization using ML

- Artificial Neural Networks (NNs)
  - Collection of nodes ("neurons")
  - Weights and biases
  - Non-linear activation function
  - Application examples: image classification, regression
- Utilize Convolutional Neural Networks (CNNs)
  - Heavily used for image recognition
  - Train model using labeled data (supervised model)
  - Replace solver call after training
  - Scanning an image, looking for patterns
  - Excels at image/pattern recognition
  - Dot product between kernel (filter) and feature combine to create feature map
- Utilizing Pytorch, an open source ML package

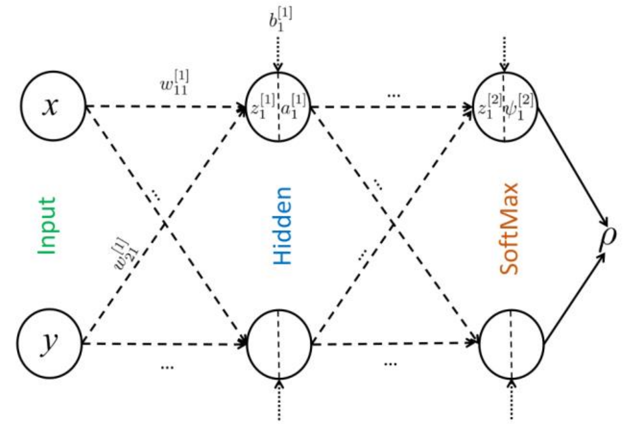
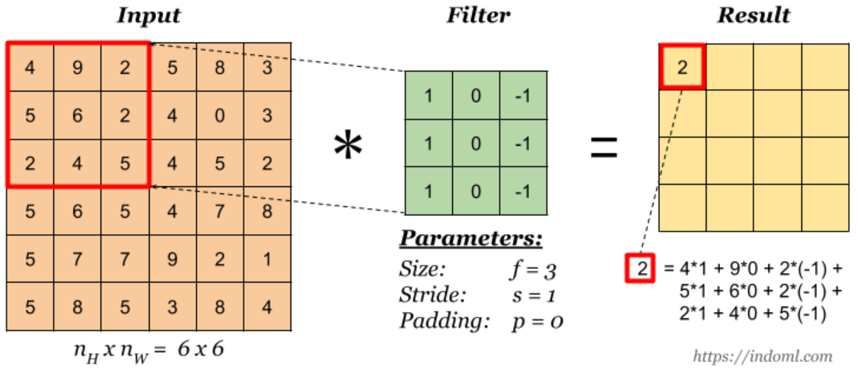


Fig. 4 Illustration of a simple network with one hidden layer of height 2

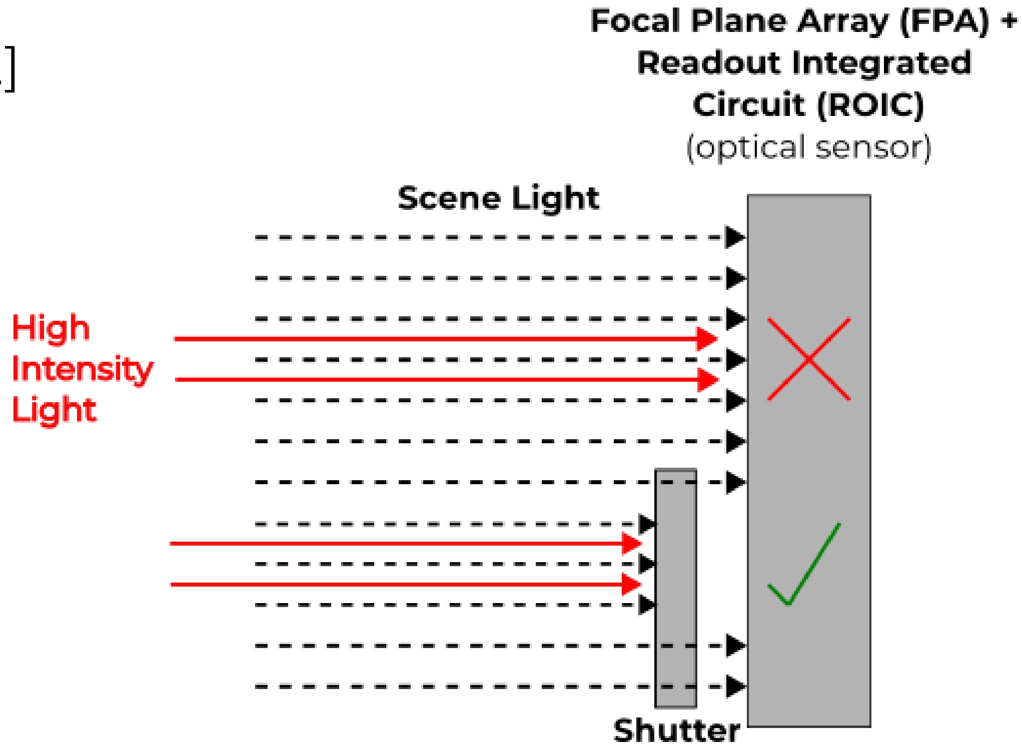
Source: Chandrasekhar and Suresh, "TOuNN: Topology Optimization using Neural Networks," https://doi.org/10.1007/s00158-020-02748-4



Source: https://medium.com/analytics-vidhya/everything-you-need-to-know-about-convolutional-neural-networks-cnns-3a82f7aa29c5

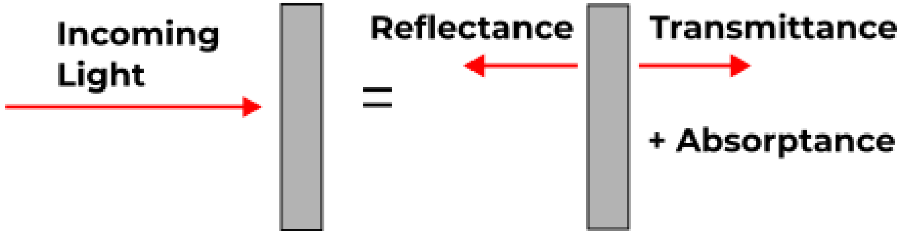
Optimization of an Optical Shutter using Machine Learning

- **Application**: sensor protection using optical shutter [1]
  - Passive
  - Thermal activation
- Utilize **Vanadium Dioxide** (**VO_2**)
  - Phase change material
- Figures of merit
  - Extinction ratio
  - Temperature rise



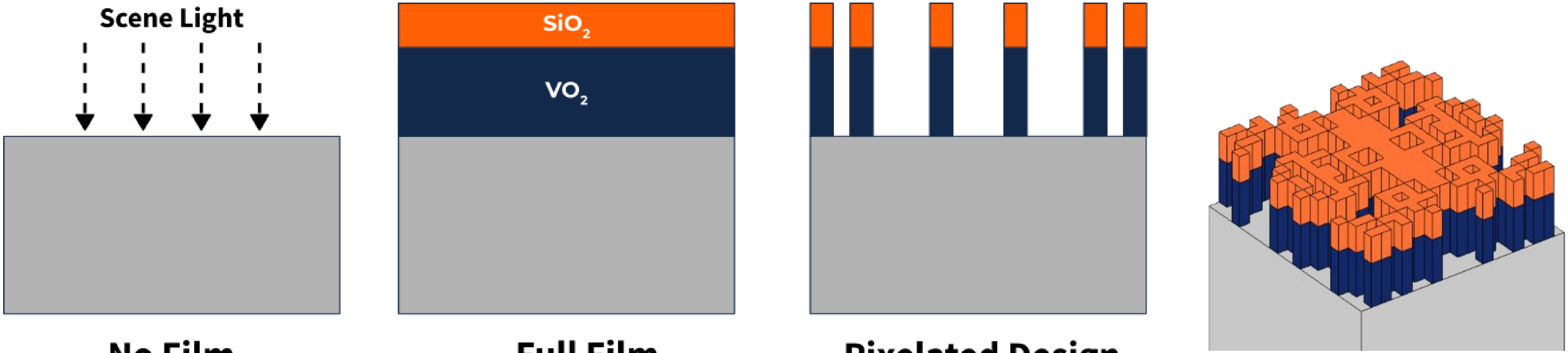
$$\text{extinction ratio} = ER = 10\log_{10}\frac{Tr_{ins}}{Tr_{met}}$$

$$\text{temperature rise} = dT = \text{Final Temperature - 273.15}$$



[1] M. G. Wood, A. McKay, T. J. Morin, D. K. Serkland, T. S. Luk, S. L. Wolfley, L. Gastian, J. P. Mudrick, B. Jasperson, and H. T. Johnson, "Optically-triggered optical limiters for short-wavelength infrared sensor protection", in 2021 Conference on Lasers and Electro-Optics (CLEO), 2021, pp. 1–2.

Design considerations



No Film
Low Extinction
No Temp Rise

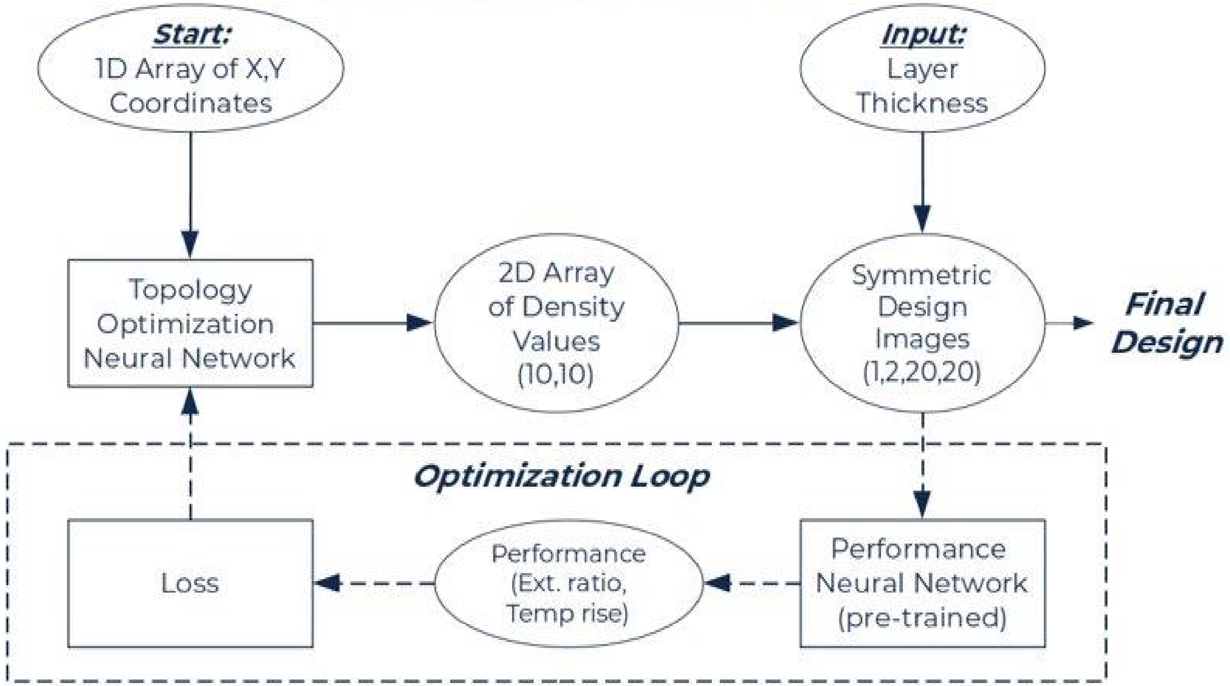
Full Film
High Extinction
Avg Temp Rise

Pixelated Design
Intermediate Extinction
Improved Temp Rise?

Can we find a pixelated design that maximizes temperature rise for a given extinction ratio?

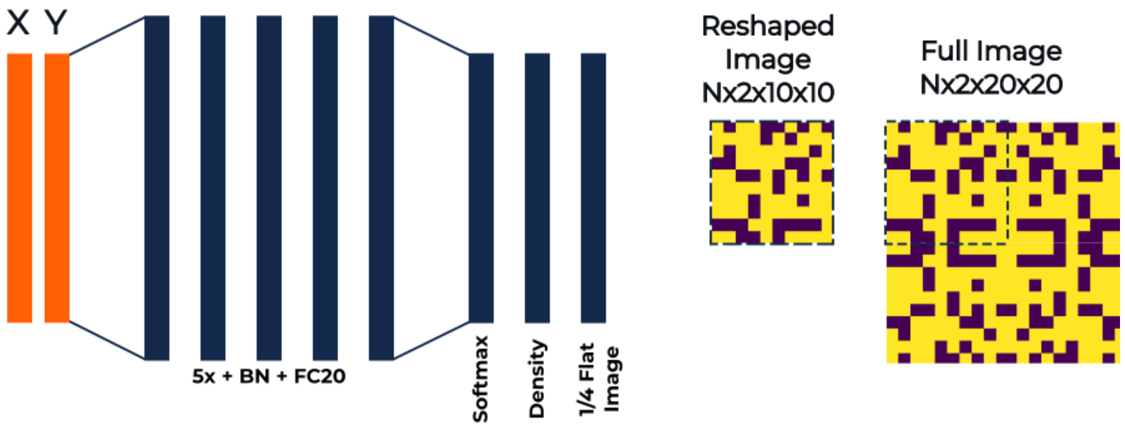
Topology Optimization Flow

Topology Optimization Flow

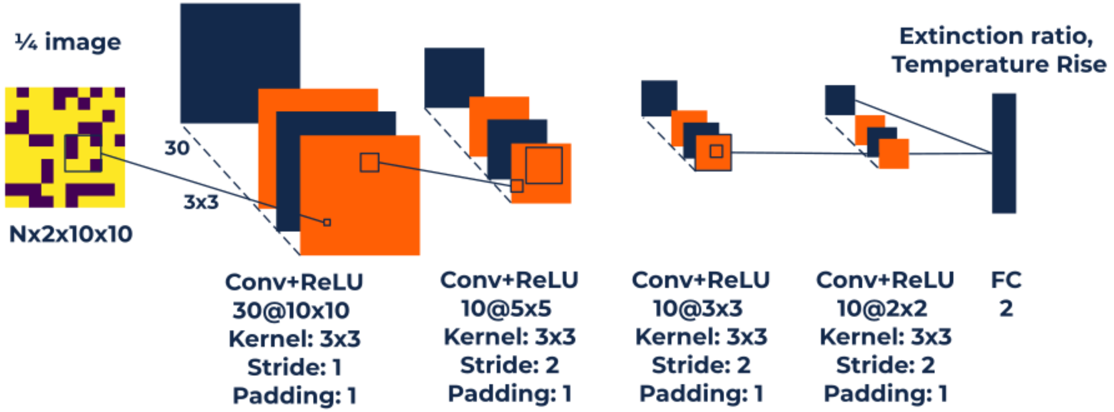


$$\text{Loss} = \left(\frac{ER_{pred} - ER_{target}}{ER_{target}}\right)^2 + \left(\frac{dT_{pred} - dT_{target}}{dT_{target}}\right)^2$$

Topology Optimization Neural Network
(5x) Batchnorm + Linear hidden layers
(20 nodes per layer)



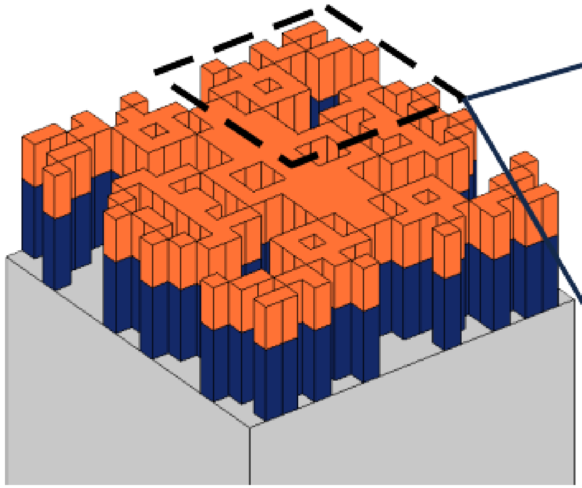
Performance Neural Network
4x Convolutional Layers + ReLU
1x Fully Connected Linear Layer



Convert Physical Design to Input Image for PerfNN

Design as Input Image

(20x20)
Symmetry about
x-axis and y-axis



(10x10) Channel 0 =
240 nm thick SiO_2

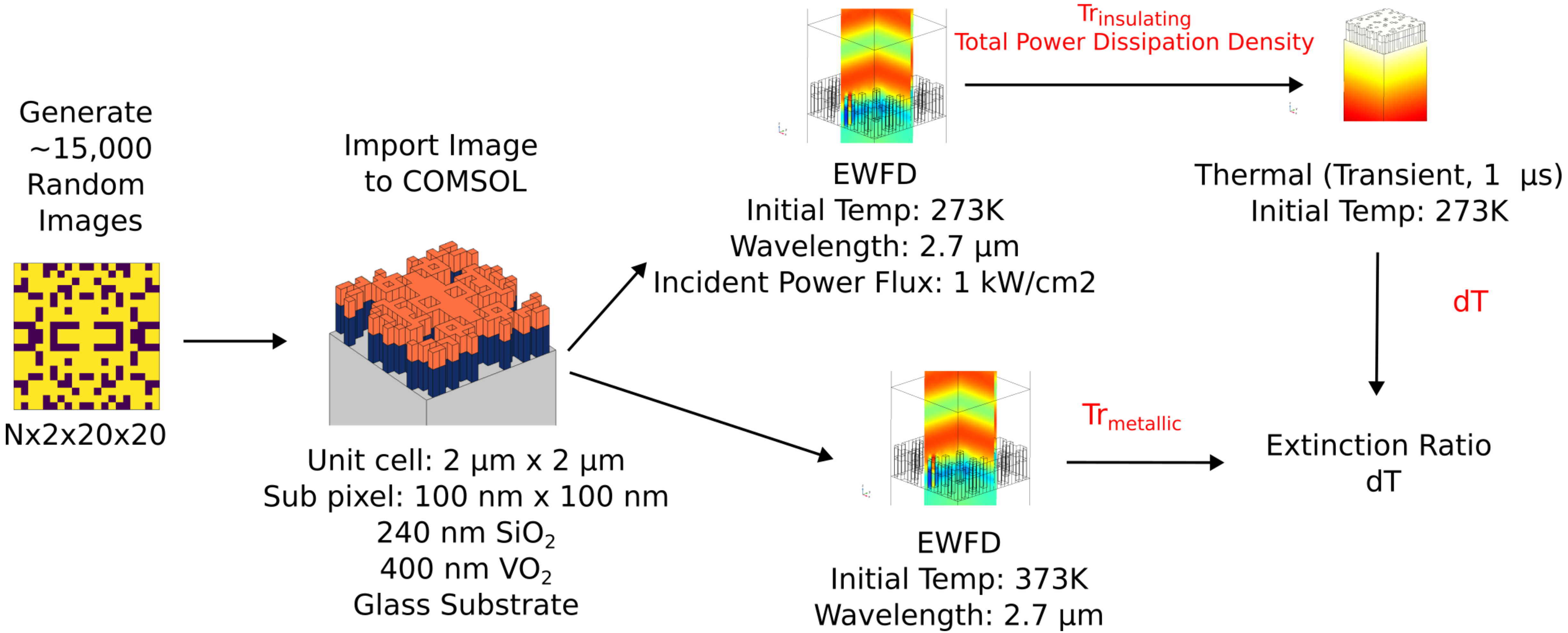
0	240	240	0	...
240	240	240	240	...
0	240	240	240	...
240	240	240	240	...
...	...	...	...	...

0	400	400	0	...
400	400	400	400	...
0	400	400	400	...
400	400	400	400	...
...	...	...	...	...

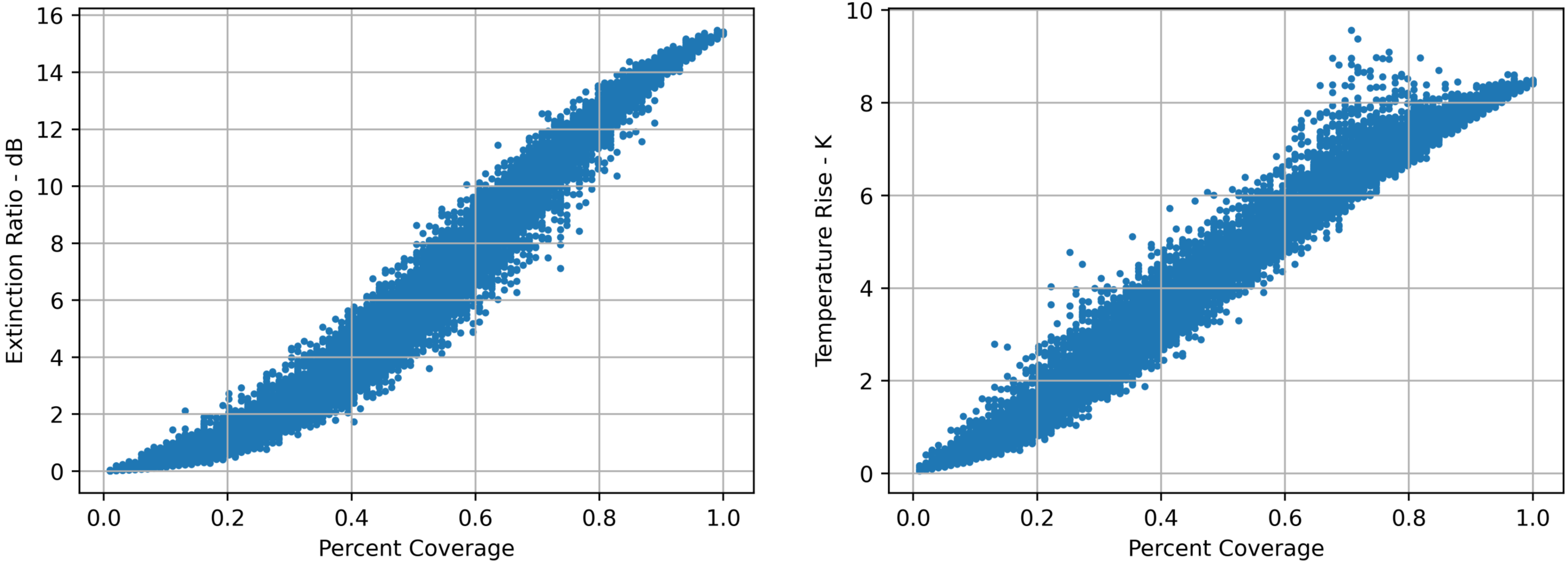
(10x10) Channel 1 =
400 nm thick VO_2

(N,2,10,10)
to PerfNN

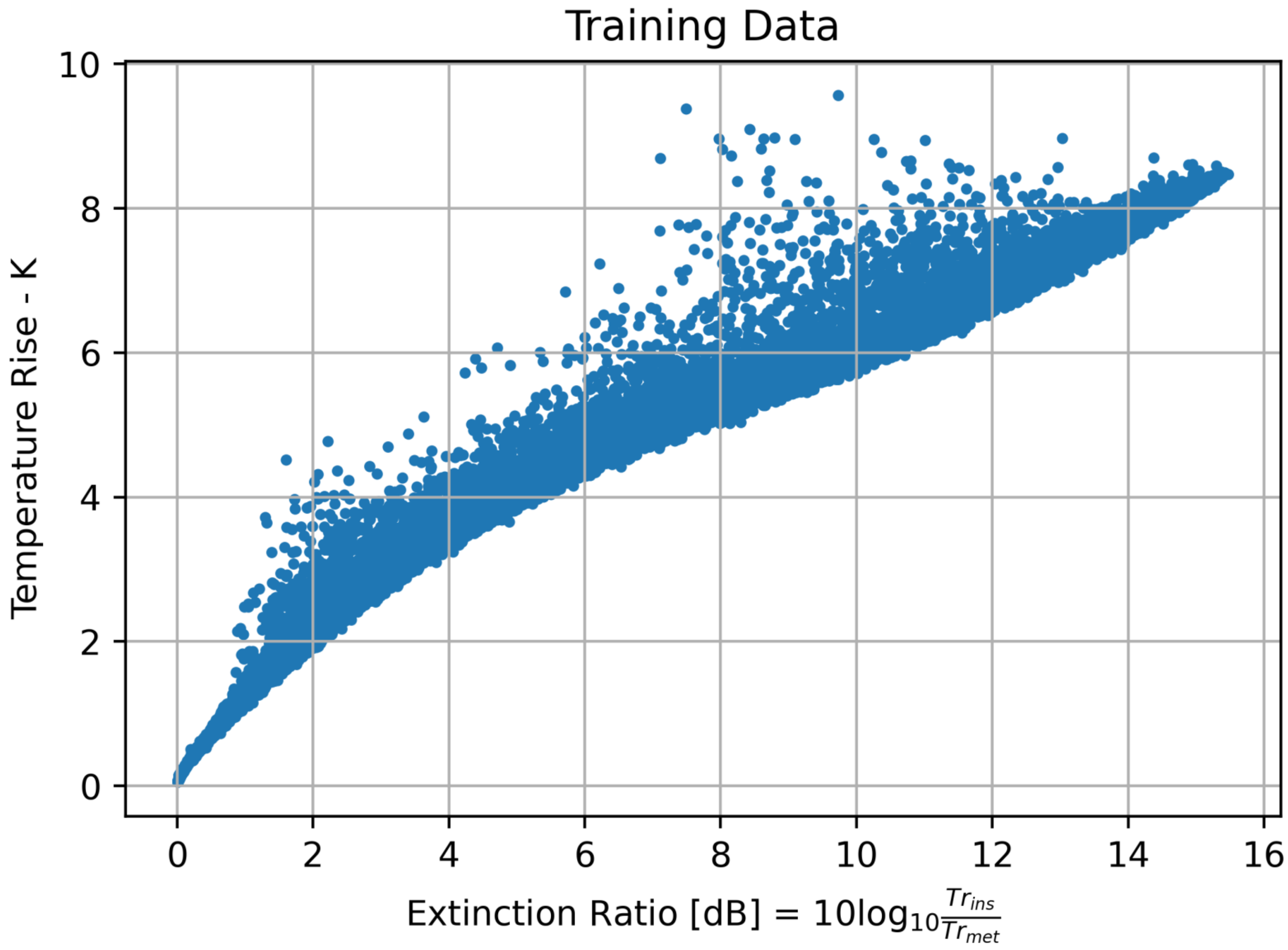
Generating Training Data with COMSOL



Generating Training Data with COMSOL



Generating Training Data with COMSOL

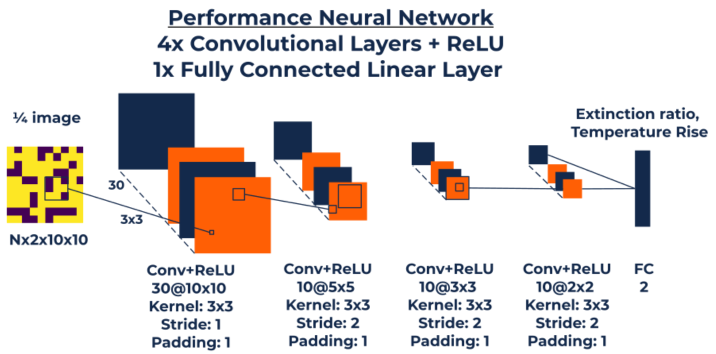


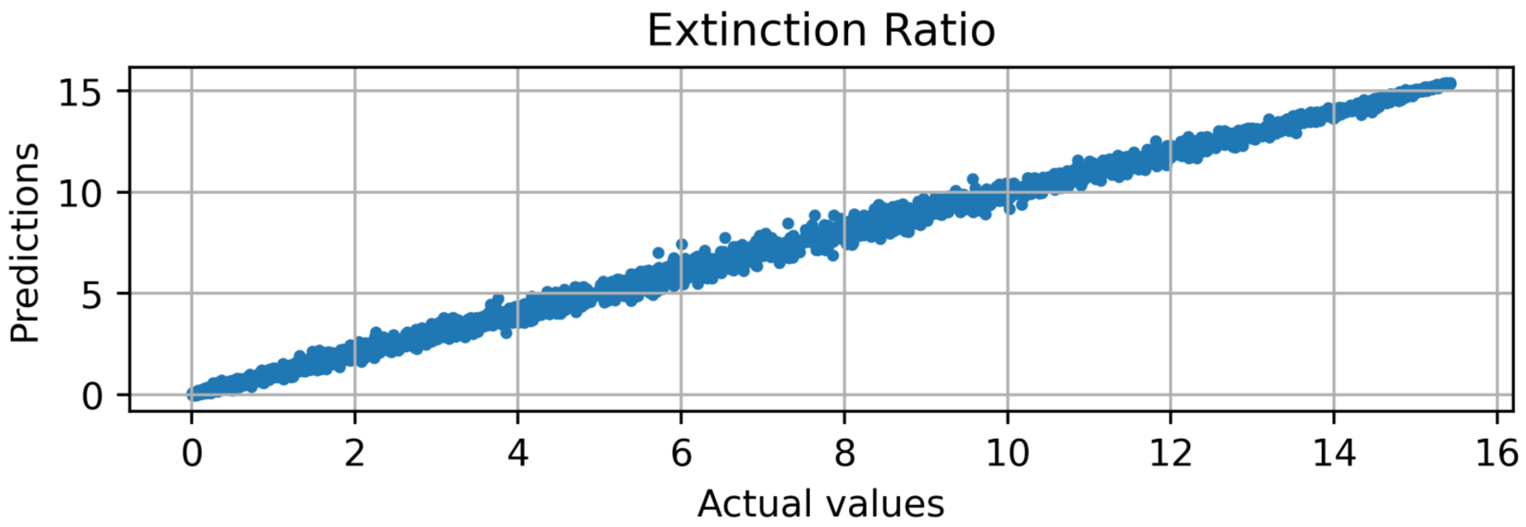
Training the Performance Neural Network

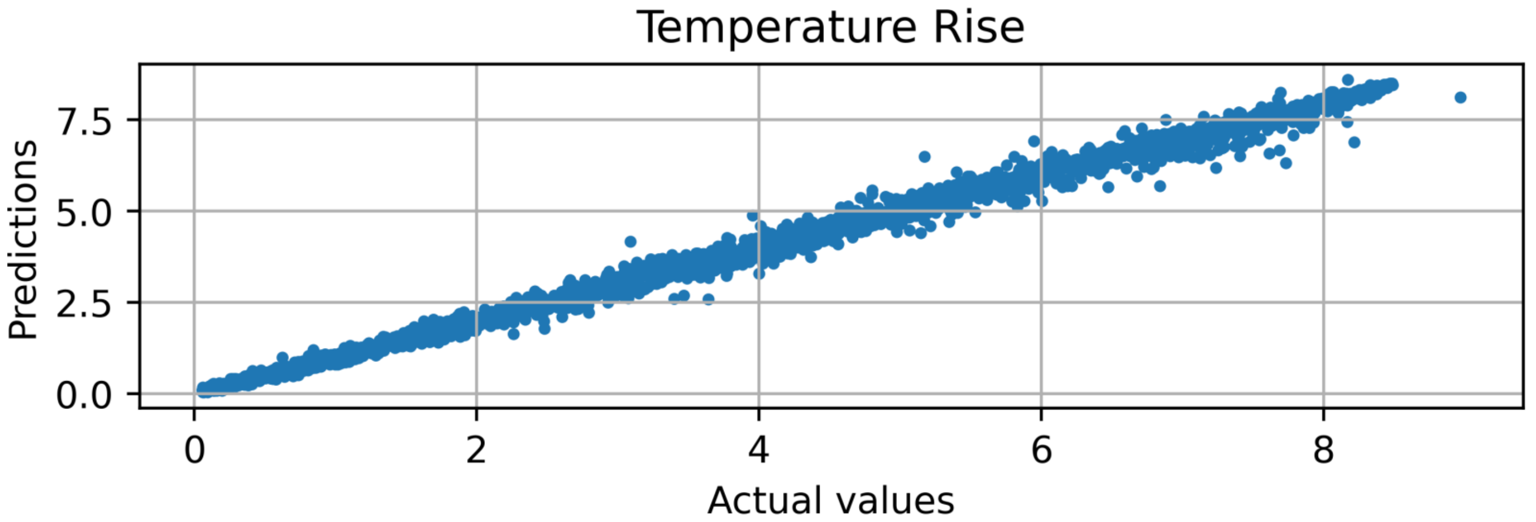
Trained performance:

- Avg abs error
  - ~13% Ext. Ratio
  - ~5.75% dT
- Maximum difference
  - ~1.44 dB ext. Ratio
  - ~1.4 K dT

Average absolute error: $\frac{1}{N}\sum_{i=1..N}\frac{|\text{pred}_i - \text{actual}_i|}{\text{actual}_i}$







Training the Topology Optimization Neural Network

Test data generated with arbitrary cost function shows good performance

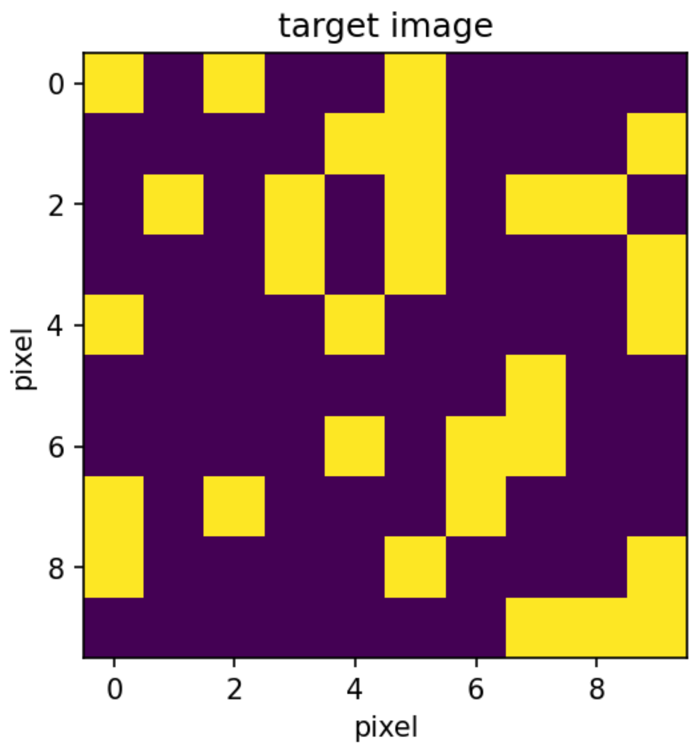
- Random "ideal" image selected
- Dummy loss function
- Translate loss into "predicted" Ext Ratio, Temp Rise

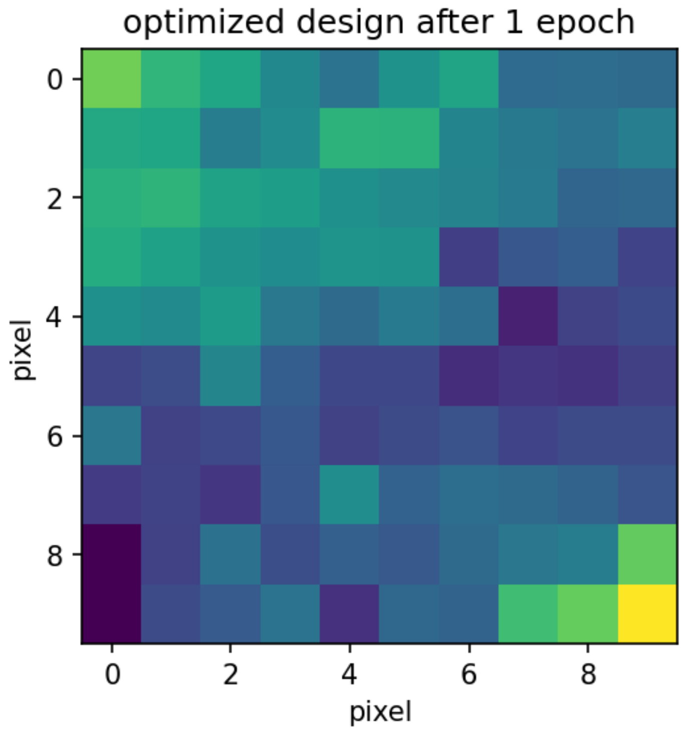
$$Loss = \sum_i \sum_j |x_{i,j} - t_{i,j}|$$

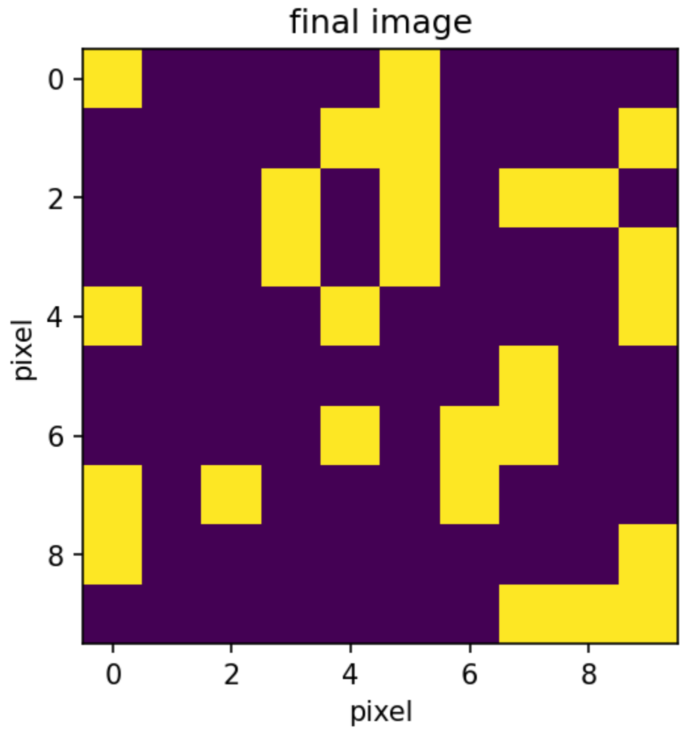
$$Tr_{insulating} = 1 - 0.5\frac{Loss}{Loss_{max}}$$

$$Tr_{metallic} = 0.5\frac{Loss}{Loss_{max}}$$

$$dT = 10\left(1 - \frac{Loss}{Loss_{max}}\right)$$

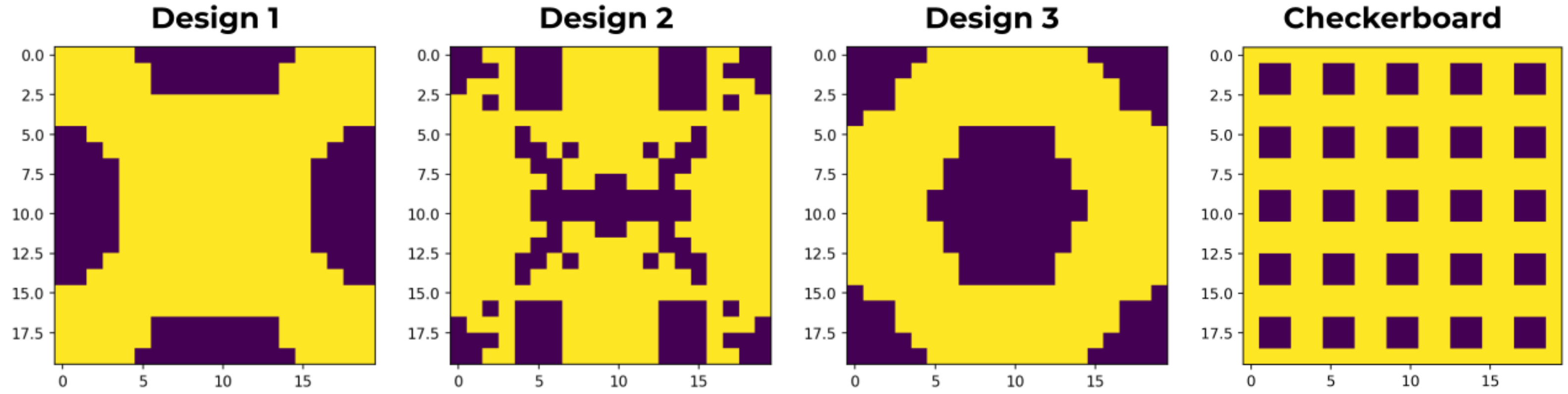


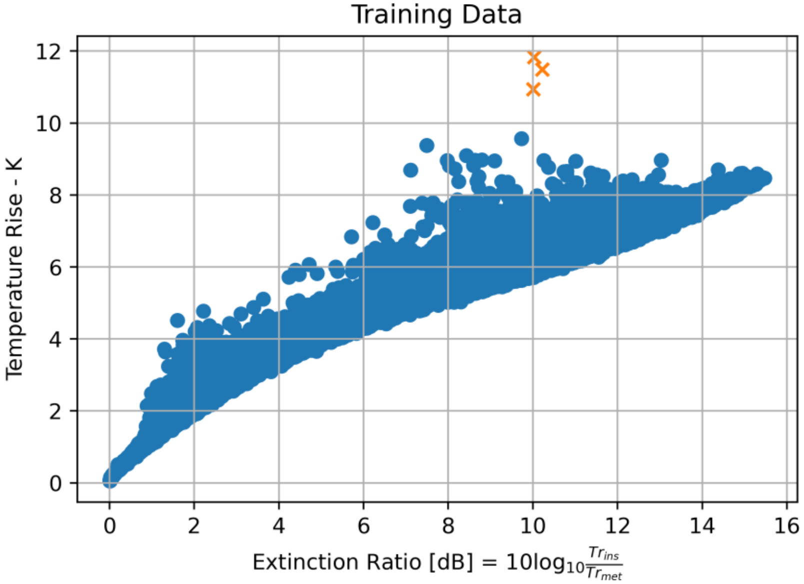




Training the Topology Optimization Neural Network

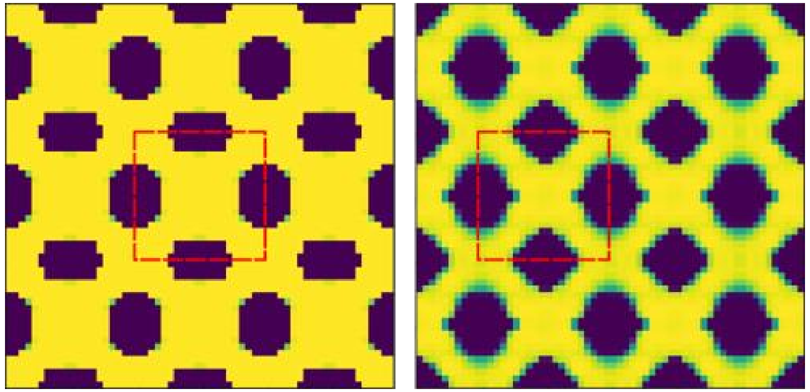
Sample Designs
(Glass Substrate + 400 VO_2 + 240 SiO_2)



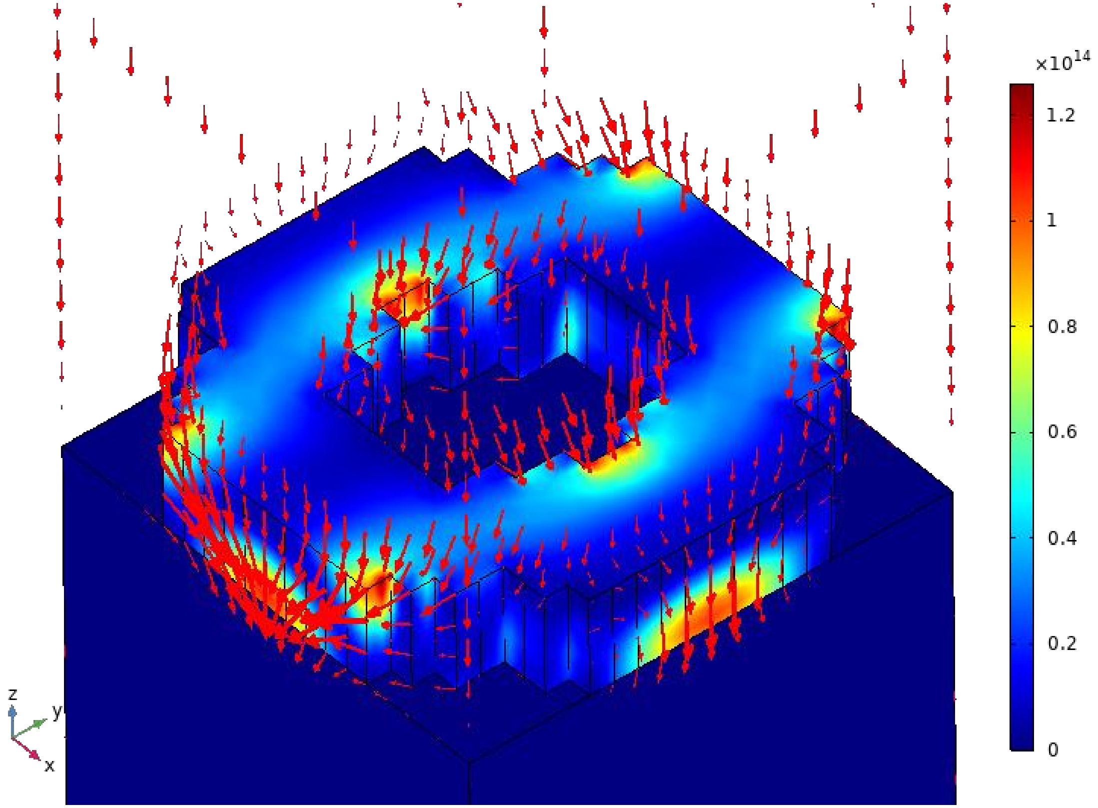


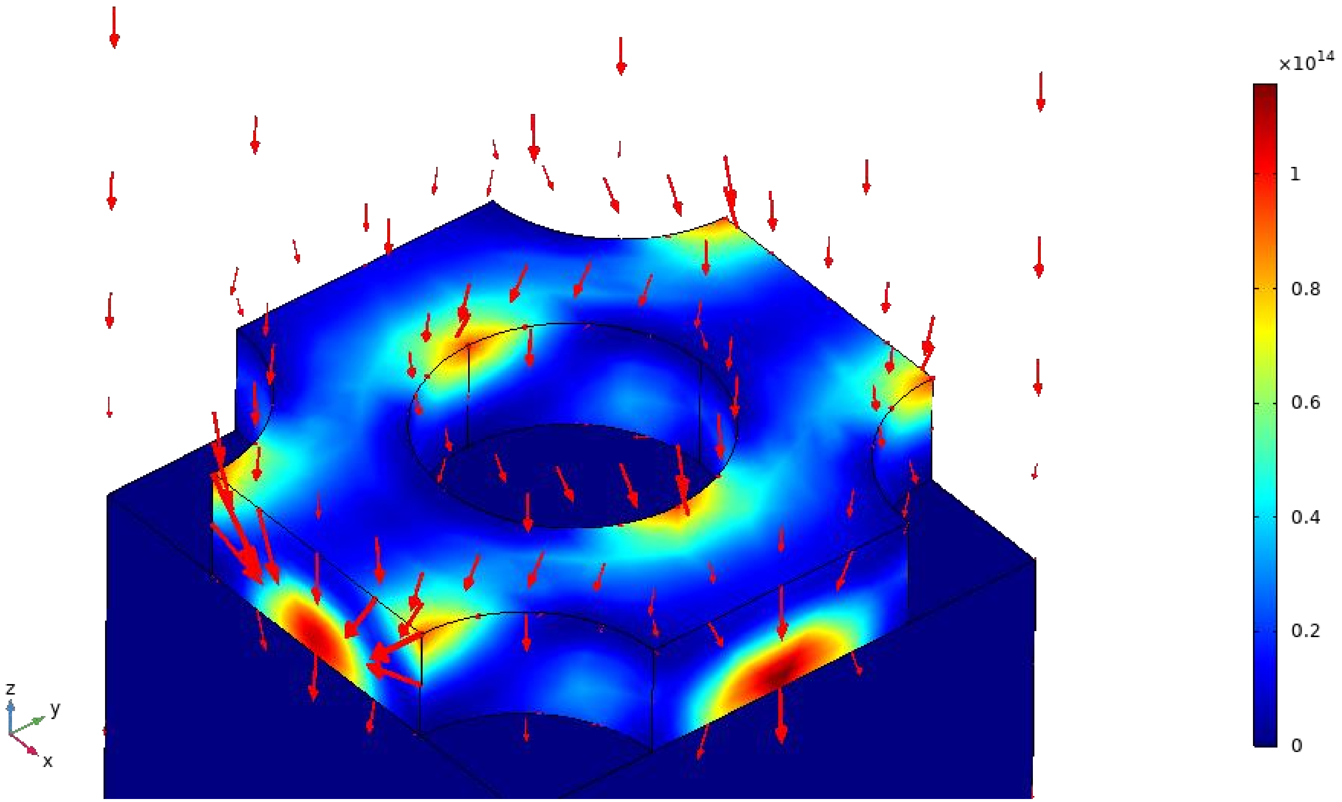
	Design 1		Design 2		Design 3		Checkerboard	Circle Array
Method	NN	COMSOL	NN	COMSOL	NN	COMSOL	COMSOL	COMSOL
Extinction Ratio	10.01	12.14	10.22	8.96	10.03	11.44	12.39	10.14
Temperature Rise	10.94	13.77	11.49	11.31	11.83	13.86	2.45	14.1
Percent Coverage	70%		68%		65%		75%	61%

Design 1 vs Design 3 (3x3 shown)



Optimized Design Performance





Volume plot: Electromagnetic Power Loss Density
Arrows: Directional Energy Flux (Poynting vector)

Poynting vector

$$\mathbf{S} = \frac{1}{2}\mathbf{E} \times \mathbf{H}^*$$

Conclusion/Future Work

- Dual neural networks for topology optimization
  - Performance Neural Network
  - Topology Optimization Neural Network
- Future work
  - Fabrication and testing of (3x) designs
  - Transfer learning: use simple model to pre-train PerfNN and use with more complex, coupled, EM/thermal time domain simulation

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Neural Network Details

- PerfNN
  - Convolutional NN
  - Four hidden layers + FC output
    - Varying number of feature maps, stride and padding
    - Activation function: ReLU
  - Output: Extinction ratio and dT
  - Loss function: MSE
  - Adam optimizer

- TopOptNN
  - Fully-connected feed-forward NN
  - Five FC hidden layers + Softmax output
    - Includes batch normalization
    - Activation function: Leaky ReLU
  - Output: first column of softmax probability distribution is used as density
  - SIMP-like constraint
    - Image = x^p [400,240]
  - Loss function: see slide
  - Adam optimizer

Training Data