Metasurface Compression Analysis via bVAE Reconstruction Loss

PURDUE UNIVERSITY
Elmore Family School of Electrical and Computer Engineering

Vaishnavi Iyer[1,3], Blake A. Wilson[1,2,3], Alexander Kildishev[3], Vladimir Shalaev[1,2,3], Alexandra Boltasseva[1,2,3]

[1]Elmore ECE Emerging Frontiers Center, USA, [2]Quantum Science Center, Oakridge National Lab, USA, and [3]Purdue University, USA

ABSTRACT

Engineering nanophotonic devices have been the focus for several data driven inverse design developments in recent years, specifically in topology optimization of photonic metastructures. In this work, we train a binary variational autoencoder (bVAE) to compress a set of discretized thermal emitter topologies into an n-dimensional binary latent space. We use the mean squared error as a measure of reconstruction loss of the bVAE against the size of the binary latent space. We find that the reconstruction loss converges to 0.027 at a binary latent space size of 100 bits.

APPLICATION EXAMPLE

Thermal Emitter Optimization

Topology optimization in non-intuitive photonic structures are difficult to optimize in high-dimensional parametric spaces.

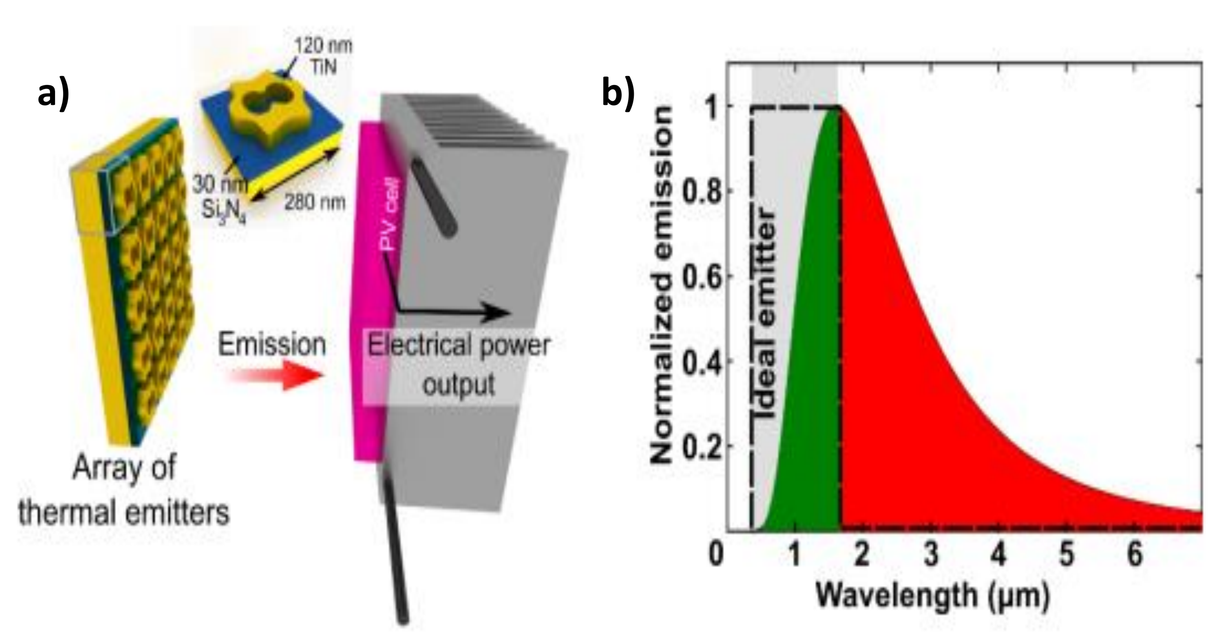
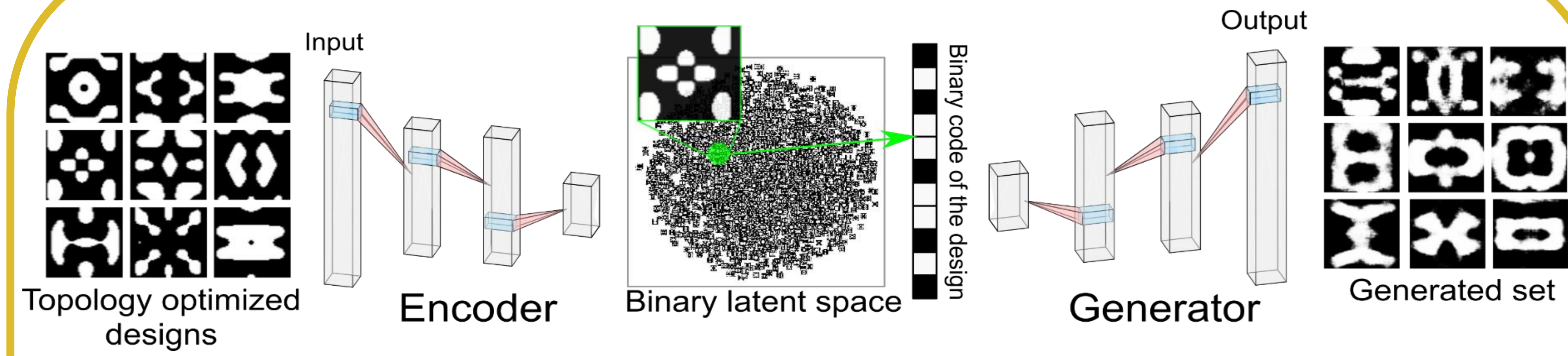


Figure 1. The objective function is the overlap efficiency between the emission spectrum of the metasurface and the absorption spectrum of the photovoltaic cell. The radiation from the array of thermal emitters is a function of the topology of the metasurface. **a)** Schematic of a thermo-photovoltaic engine where the left metasurface array radiates onto the photovoltaic cell. **b)** The solid line is a black body radiation curve at 1800-°C; The black dashed line corresponds to an ideal thermal emitter's emissivity and the absorption spectrum of the photovoltaic cell.

BINARY VARIATIONAL AUTOENCODER (bVAE)



$x_n \in \{0,1\}^k$ $\hat{y}_n \in \{0,1\}^m$ $\hat{x}_n \in \{0,1\}^k$

MSE Reconstruction Loss

$$T(x) = \sum_{n=1}^{N} |\hat{x}_n - x_n|^2 \quad (1)$$

where x_n is a discretized input metasurface, $\hat{x}_n$ is the reconstructed metasurface from the bVAE, and N denotes the size of metasurface dataset.

Latent Space Compression Ratio

An ideal bVAE is an invertible map $g: \{0,1\}^k \to \{0,1\}^m$ between the topology design space of size 2^k and the latent space of size 2^m. Therefore, the compression ratio γ between these two spaces can be written as:

$$\gamma = 2^{k-m}. \quad (2)$$

MSE LOSS AGAINST LATENT SPACE COMPRESSION

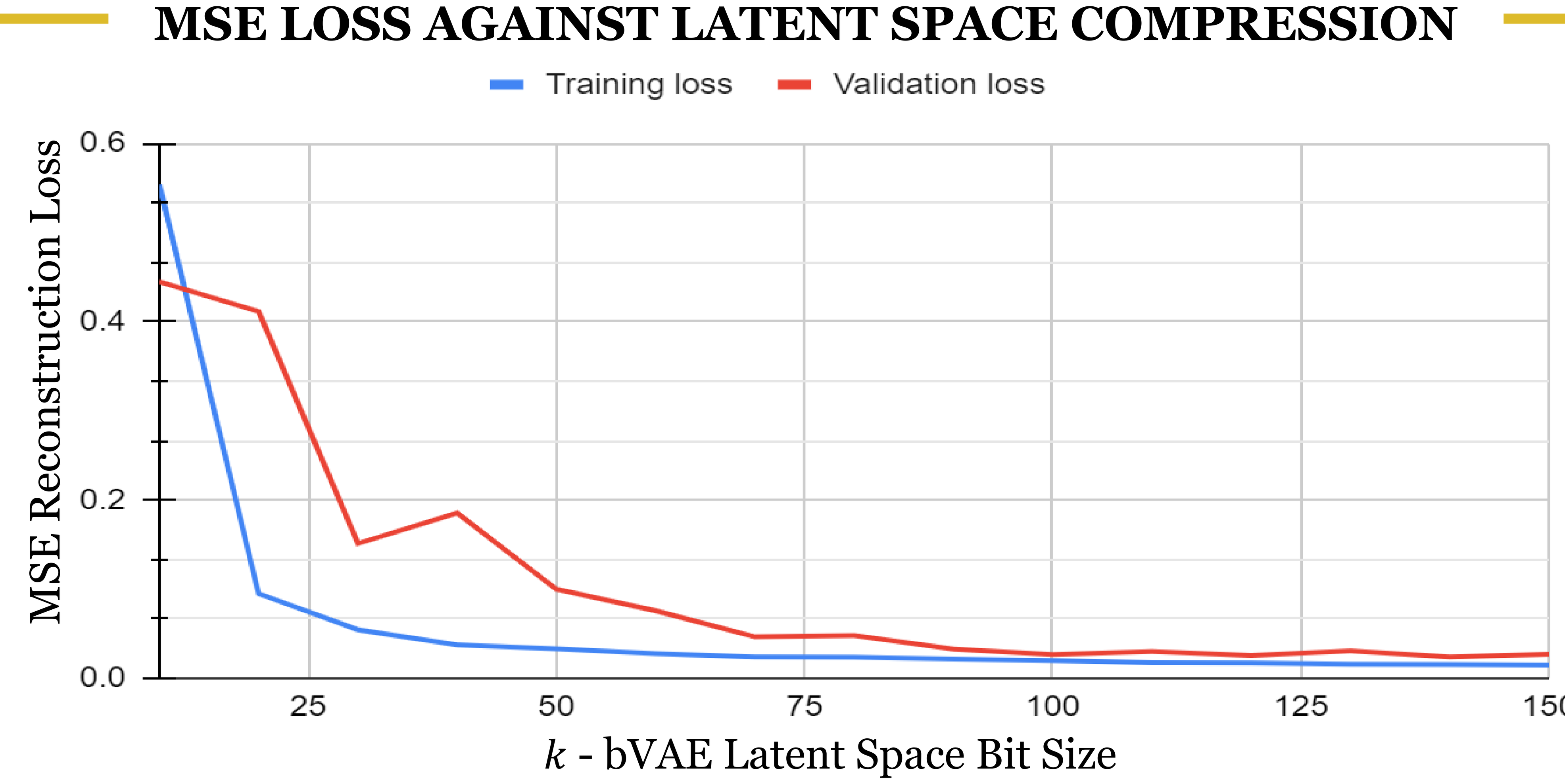


Figure 2. The reconstruction loss for both the training set (blue) and the validation set (red) is measured as a function of the number of bits k in the latent space vector of the bVAE. Using (2), we can compute the relation between the bit size and the compression ratio as $k = \log \gamma + m$.

ALGORITHM

1) Split dataset into training, testing, and validation datasets.
2) For m from 10:10:150 :
   1) For each training epoch
      1) Train bVAE
      2) Measure reconstruction loss of testing dataset using (1).
   2) Measure reconstruction loss of validation testing set using (1).

DISCUSSION

- By analyzing the tradeoff between reconstruction loss and binary latent space size, we can explore the limitations of optimizing the thermo-photovoltaic problem using quantum optimization.
- When discretizing continuous space optimization problems, it's important to consider the reconstruction loss, i.e., accuracy of discretized compression, vs problem size.
- By considering different latent space sizes, we can observe asymptotic behavior at each instance.

CONCLUSION

- As the latent space size increases with increasing bit size, the reconstruction loss decreases inversely with the compression ratio, showing more accurate reconstruction.
- This analysis is scalable for different applications of metasurfaces and can bolster their applications in different areas of thermal optimization.

REFERENCES

Wilson, B., & Kudyshev, Z. (2021, May). *Machine Learning Framework for Quantum Sampling of Highly-Constrained, Continuous Optimization Problems.* https://arxiv.org/abs/2105.02396

Kudyshev, Z., Kildishev, A., Shalaev, V., & Boltasseva, A. (2020, March). *Machine Learning-Assisted Metasurface Design for High-Efficiency Thermal Emitter Optimization.* https://arxiv.org/ftp/arxiv/papers/1910/1910.12741.pdf

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