Inverse Design of Multilayer Thin film by Deep Neural Network

Preetam Kumar

Electrical Communication Engineering
Indian Institute of Science
Bangalore, India
preetamkumar@iisc.ac.in

E.S.Shivaleela

Electrical Communication Engineering
Indian Institute of Science
Bangalore, India
lila@iisc.ac.in

Fekadu Mihret

Electrical Communication Engineering
Indian Institute of Science
Bangalore, India
fekadug@iisc.ac.in

Arpita Mishra

Electrical Communication Engineering
Indian Institute of Science
Bangalore, India
arpitamishra@iisc.ac.in

T.Srinivas

Electrical Communication Engineering
Indian Institute of Science
Bangalore, India
tsrinu@iisc.ac.in

Abstract—Inverse Design of TiO_2-SiO_2 based multilayer thin film for normal incidence of TM polarized light in visible region by Deep Neural Network is reported. The simulated and the target transmission spectra are closely following .

Index Terms—Inverse Design, Optical Filter, Deep Neural Network, Multilayer thin Film

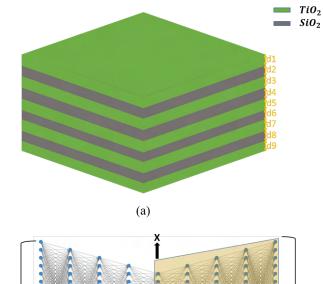
I. INTRODUCTION

Multilayer thin films are one of the key components in photonic circuits. Designing of these multilayer thin films requires comprehensive mathematical analysis and computationally expensive numerical methods [1].

In recent years, Inverse Design(ID) methods enables the automation of designing complex nanophotonic structures. This enables the utilization of full design parameters for a desired target response [2]. However the numerical methods such as fdfd, fdtd with adjoint optimization makes the conventional ID methods computationally expensive [3].

To overcome these issues, Deep learning becomes an suitable tool to accelerate the design process [4]. Deep neural network is a data driven approach. In this method, first a sufficient amount of data is generated and then model is trained by these data. These trained model can predict output instantly for a given input set.

In this paper we have used Tandem neural network architecture(TNN) [5] for ID of TiO_2-SiO_2 based 9 layer thin film as shown in Figure I. Here, thickness of each layer is the design variable and transmission response in the visible region is the target spectrum. TNN predicts the thickness of each layer for a given target response.



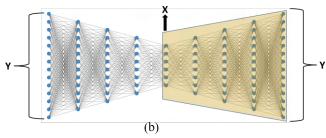


Fig. 1. (a) shows the schematic of the 9 layer thin film. Here each layer thickness $d_{i(1,2,...9)}$ is the design parameter for the target response.(b) shows the schematic diagram of the TNN. Here X is the set of thickness of the layers and Y is the set of corresponding transmission spectrum. The shaded part in the TNN is the forward model whose trainable parameters are frozen after the first stage of the training.

II. RESULT AND DISCUSSION

We have generated 75000 data sets for training and 25000 data sets for validation of the neural network. Each data set comprise of thickness of the 9 layer with respective transmission response. TNN architecture is a combination of forward

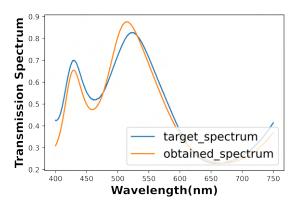


Fig. 2. Spectrum obtained and target spectrum from test data 1

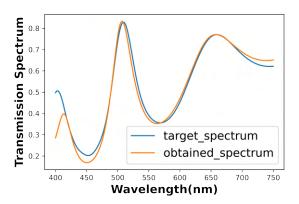


Fig. 3. Spectrum obtained and target spectrum from test data 2

model and inverse model. Training of the TNN is done in two stages. In the first stage, the forward model is trained with thickness set(X) of the thin film device as the input parameter and transmission spectrum(Y) as the output parameter. After the training, the trainable parameter of the forward model is frozen and combined with the inverse model. In the second stage of the training, the combined architecture is trained with the transmission spectra(Y) as the input parameter and the thickness sets(X) as the output parameters of the inverse model. In the second stage of the training, only the trainable parameter of the inverse model is updated. Hence, both input and output of the combined network are the transmission spectrum. After the training, TNN predicts the thickness of each layer with corresponding target spectrum.

We have designed the TiO_2 - SiO_2 based thin film for multiple target spectrum as shown in Figure 2-5.

The thicknesses(in nm) obtained for the corresponding target spectrum are as follows:

t1=[164, 120, 109, 144, 103, 174, 25, 42, 136] t2=[119, 117, 184, 150, 132, 105, 97, 142, 129]

t3=[247, 129, 84, 139, 163, 113, 55, 205, 221]

t4=[275, 86, 227, 187, 172, 295, 119, 298, 184]

Figure 2,3 shows the predicted spectrum closely follow the

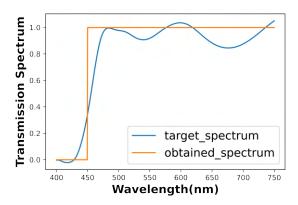


Fig. 4. Spectrum obtained and target spectrum as High Pass Filter(HPF)

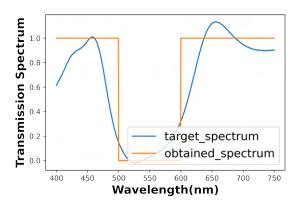


Fig. 5. Spectrum obtained and target spectrum as Band Stop Filter(BSF)

deep and high of the target spectrum. The thicknesses obtained for the corresponding target spectrum t1 and t2 respectively, We also designed the thin film as filter as shown in Figure 4,5. The thicknesses obtained for BSF and HPF are t3 and t4 respectively. Figure 4 shows the predicted spectrum has ripples within 20% of the target transmission in pass band. Figure 5 shows the predicted spectrum has 20% below transmission for rejection band(500nm-600nm) and small ripples in the pass band.

III. CONCLUSION

By using the TNN, different set of thicknesses are obtained in all the cases by the inverse model and obtained spectrum closely matches with the target spectrum.

REFERENCES

- Acquaroli, L.N., 2018. Matrix method for thin film optics. arXiv preprint arXiv:1809.07708.
- [2] Molesky, Sean, et al. "Inverse design in nanophotonics." Nature Photonics 12.11 (2018): 659-670..
- [3] Lalau-Keraly, Christopher M., et al. "Adjoint shape optimization applied to electromagnetic design." Optics express 21.18 (2013): 21693-21701.
- [4] Wiecha, Peter R., et al. "Deep learning in nano-photonics: inverse design and beyond." Photonics Research 9.5 (2021): B182-B200.
- [5] Zhen, Zheng, et al. "Realizing transmitted metasurface cloak by a tandem neural network." Photonics Research 9.5 (2021): B229-B235...