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A Study on Machine Learning Assisted Accelerated Design of Microwave Structures

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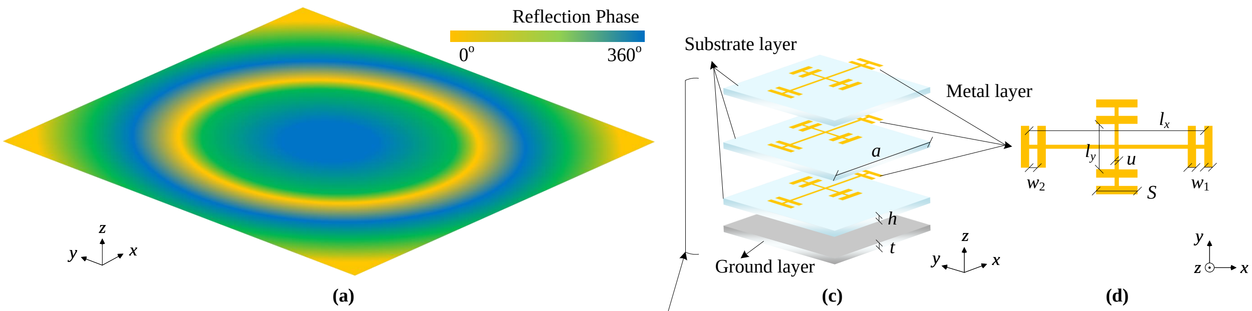
Abstract— An increasing number of researchers devote to applying machine learning for accelerating design of microwave structures (e.g., antenna, metasurface, filter, etc.), inspired by the great potential that machine learning shows in many fields, such as image/speech/digits recognition, self-driving, text processing, etc. Despite the fact that machine learning based design has been widely validated to be accurate and well-behaved, machine learning based design methods are often doubted in terms of efficiency, because a large amount of simulation works are mandatory to be executed previously for preparing sufficient training data. In that sense, machine learning based design seems not to be efficient, as it takes more simulation works in total than conventional optimization algorithm based design methods. This paper investigates the efficiency of machine learning based design compared with typical optimization algorithm based design, and a generic solution is proposed for reducing the burden of data preparation to improve the efficiency of machine learning based design. By qualitatively analyzing the required simulation cycles during the whole design process, we propose efficiency measures to demonstrate and compare the efficiency of machine learning based design and typical optimization algorithm based design in the context of metasurface design. According to the comparison result, machine learning based design outperforms other methods in terms of efficiency when it comes to high-bit metasurface design, while optimization algorithm based design is more efficient for low-bit metasurface. Based on the observation, we introduced an improved design approach that combines the advantages of optimization algorithms and machine learning. The qualitative analysis and improved design approach may also bring inspiration to the design of other microwave structures. Investigating on improved data acquisition method for reducing required simulation and training data is a promising direction for further boosting machine learning based accelerated design of microwave structures.

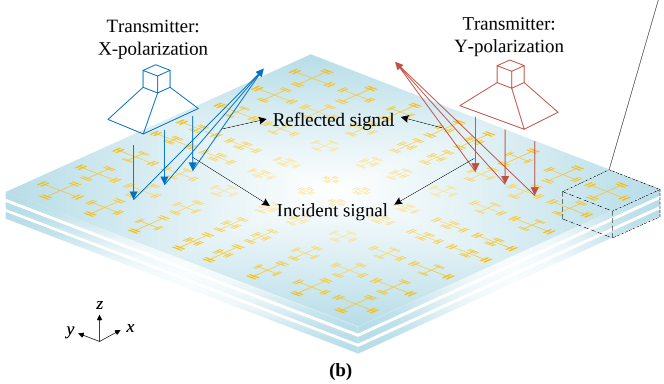
1. INTRODUCTION

Microwave structures, such as antennas and metasurfaces, are widely used in various applications such as wireless communication, medical imaging, and radar. These structures need to be carefully designed to adjust their electromagnetic coefficients, such as transmission, reflection, gain, and axial ratio, to meet specific requirements in different scenarios. However, the relationship between geometrical parameters and electromagnetic coefficients cannot be expressed using closed-form equations, making it difficult to design such structures. Currently, experienced human engineers manually adjust the geometrical parameters and iteratively simulate the EM coefficients to achieve optimal designs. This process is labor-intensive and relies heavily on the engineer's experience level.

To reduce the need for experienced engineers, optimization algorithms such as genetic algorithms and particle swarm optimization have been used to assist the design of EM structures for decades. These methods upgrade an initialized population of randomly generated designs iteratively until an optimal design is achieved. The designs are evaluated through simulation, and then the next generation population is generated based on the evaluation. The main difference between optimization algorithm-based methods is how they generate the next generation designs.

Recently, machine learning-based methods for automated design of microwave structures have attracted significant attention due to the incredible potential of machine learning in various fields. These methods require a large amount of simulation cycles for collecting training data to develop a surrogate model. Based on how the model is trained and applied for future design, they are categorized as inverse models, forward models, and generative models. Inverse models determine the suitable geometric parameters according to the given EM constraints, while forward models are





GEOMETRIC PARAMETERS

Parameter	Value (mm)	Parameter	Value (mm)
l_x	[1.9, 4.4]	u	0.1
l_y	1.1	S	1
w_1	0.2	h	2
w_2	0.2	t	0.017
a	5		

(e)

Figure 1: (a) Desired reflection phase distribution; (b) MJC metasurface; (c) 3D view of its unit cell; (d) up view of its metal layer; (e) geometric parameters of the unit cell [4].

trained in the opposite direction. Generative models capture the key features using only geometric parameters, and neither forward nor generative models can be directly used to determine optimal designs. They are usually integrated with an optimization process to evolve into an optimal design iteratively.

While machine learning-based design methods are highly accurate, they require a large amount of pre-simulation for collecting training data, leading to doubts regarding their efficiency. In comparison, optimization algorithm-based methods seem to reach similar designs using fewer simulations. Despite this, many studies have shown that well-trained machine learning models can significantly assist in future designs.

This paper studies on the efficiency of machine learning and compares with optimization algorithm-based methods in the context of multi-bit metasurface design. The proposed efficiency measures suggest that machine learning outperforms optimization algorithm-based methods for the design of high-bit metasurfaces. It might be extended to that the efficiency of machine learning increases as the number of design tasks within the same solving space increases.

2. STUDY ON EFFICIENCY

In [4], the Modified Jerusalem Cross (MJC) reflective metasurface is capable of independently controlling signals with orthogonal polarization. The desired ideal continuous phase distribution for compensation is depicted in Fig. 1(a), but it cannot be practically achieved using an infinite number of bits and unit cells. Therefore, a compromise is to use a n-bit metasurface, as shown in Fig. 1(b), where a larger n results in a higher resolution approximation. The n-bit metasurface is divided into N_g groups, with unit cells in each group having identical geometries but modified to provide different phase compensation states. Each MJC unit cell (Fig. 1(c)) consists of three dielectric (F4B) layers, three metal MJCs on top, and a full metal ground layer, with geometric parameters listed in Fig. 1(e). The MJC is made up of two perpendicular metal bars (Fig. 1(d)), with the length of each bar (l_x/l_y) adjustable to tune the reflective phase (ϕ_x/ϕ_y) of the corresponding polarization. Zhu *et al.* specifically adjusted the length of the bar in the x direction (l_x) to control the reflective phase in x-polarization, and the same can be done for the bar in the y direction.

Zhu *et al.* developed an ML-based method to expedite MJC metasurface design. The model

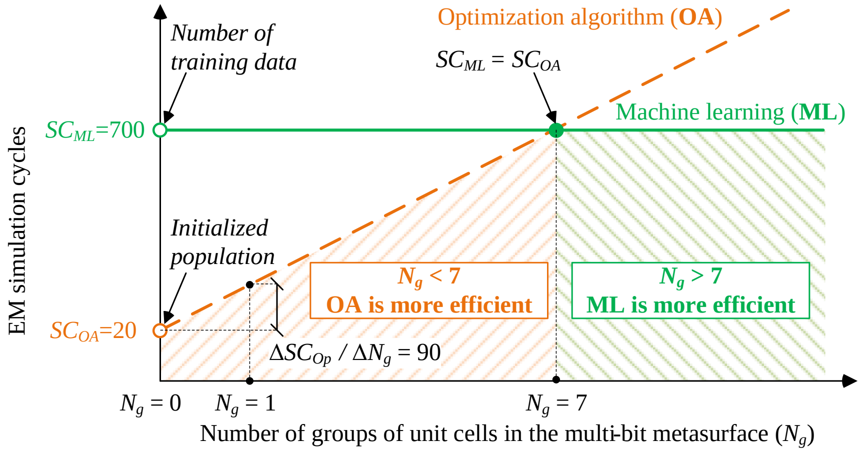


Figure 2: The proposed efficiency measures.

consists of an input layer taking ϕ_x, a hidden layer of 20 neurons, and an output layer generating l_x. The loss function is the MSE between predicted and actual l_x, and Levenberg-Marquardt is the backpropagation algorithm. 700 simulation cycles collected the training data by sweeping l_x from 1.9 mm to 4.4 mm, and extra 300 simulation cycles generated validation/test data. As reported in [4], the well-trained ML model can determine l_x directly based on ϕ_x with an error range of ± 0.01 mm. We define SC_{ML} as 700, which is the minimum needed for the model to function. The extra 300 simulation cycles are excluded.

To compare with optimization algorithm-based methods, we use genetic algorithm to design MJC unit cells with the built-in genetic algorithm tool in Computer Simulation Technology®(CST). We initialize 20 geometries by randomly setting l_x at 20 values from 1.9 mm to 4.4 mm, with a mutation rate of zero. Each of the 20 geometries is individually simulated and evaluated based on the simulation results and the target ϕ_x. The top 10 geometries are inherited in the next iteration, from which 10 new geometries are reproduced. This results in 20 geometries in the new iteration, and only the new 10 geometries are simulated and evaluated. The evaluation results are compared with the old 10 geometries to select the best 10 geometries for the new iteration. This iterative process of inheriting, reproducing, and evaluating continues until one geometry fits the target ϕ_x within ± 0.01 mm error range. In addition to the initialization, the average number of simulation cycles required during optimization is 90. For example, if $N_g = 1$, the total number of simulation cycles required is 110 ($= 20 + 90$), which includes the number of simulation cycles required for initialization (20) and during optimization (90); if $N_g = 2$, the total number of simulation cycles required is 200 ($= 20 + 90 + 90$), which only increases due to the additional simulation cycles required during the optimization process for the second target ϕ_x. We choose genetic algorithm as a representative of optimization algorithm-based methods because it is a commonly used optimization algorithm in electromagnetic design.

The efficiency measures for MJC metasurface design are presented in Fig. 2. From the plot, it can be seen that the green curve, which represents ML-based design, intersects with the orange curve, which represents genetic algorithm-based design, at approximately $N_g = 7$. This indicates that ML-based design outperforms genetic algorithm-based design for N_g values greater than 7, while genetic algorithm-based design is more efficient when N_g is less than or equal to 7.

3. CONCLUSION

We investigate on and compare the efficiency of machine learning-based methods with other optimization algorithm-based methods for the design and analysis of electromagnetic structures in this paper. The investigation and comparison are carried on the design process of a multi-bit metasurface. A multi-bit metasurface consists of multiple groups of various microwave unit cells within a geometry space. Machine learning-based methods approximate a function that projects the geometry combinations to the electromagnetic responses within a continuous space, by training a surrogate model using discrete training samples within the continuous space. By contrast, optimization algorithm-based methods upgrade a population of geometries iteratively to arrive at an optimal design that satisfies a specific electromagnetic constraint. Therefore, the proposed efficiency measures suggest that machine learning-based methods show higher overall efficiency for the design of high-bit metasurfaces, while optimization algorithm-based methods outperform regarding efficiency when it comes to the design of low-bit metasurfaces. This observation may be extended to the design of other microwave structures. The overall efficiency depends on the number of design tasks within the same parameter space, such as a series of antennas with the same topology.

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REFERENCES

1. S. Cui and D. S. Weile, "Robust design of absorbers using genetic algorithms and the finite element-boundary integral method," *IEEE Trans. Antennas Propag.*, vol. 51, no. 12, pp. 3249–3258, Dec. 2003, doi: 10.1109/TAP.2003.820971.
2. F. Afshinmanesh, A. Marandi, and M. Shahabadi, "Design of a single-feed dual-band dual-polarized printed microstrip antenna using a boolean particle swarm optimization," *IEEE Trans. Antennas Propag.*, vol. 56, no. 7, pp. 1845–1852, Jul. 2008, doi: 10.1109/TAP.2008.924684.
3. Z. Zhou, Z. Wei, J. Ren, Y. Yin, G. F. Pedersen and M. Shen, "Representation learning-driven fully automated framework for the inverse design of frequency-selective surfaces," *IEEE Trans. Microw. Theory Techn.*, early access, 2023, doi: 10.1109/TMTT.2023.3235066.
4. R. Zhu, J. Wang, Y. Han, S. Sui, T. Qiu, Y. Jia, M. Feng, X. Wang, L. Zheng, and S. Qu, "Design of aperture-multiplexing metasurfaces via back-propagation neural network: Independent control of orthogonally-polarized waves," *IEEE Trans. Antennas Propag.*, vol. 70, no. 6, pp. 4569–4575, Jun. 2022, doi: 10.1109/TAP.2022.3140523.