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# A Generative Optimization Method for Reflectarray Antennas Combining Self-Supervised Learning and Transfer Learning

Hao Huang and Xue-Song Yang*

*School of Physics, University of Electronic Science and Technology of China, China*

**ABSTRACT:** A hybrid machine-learning-based optimization method is proposed for the quick optimization of antenna shape design. The hybrid optimization method combines self-supervised learning (SSL) and transfer learning (TL). The application of SSL avoids the requirement to obtain labeled simulation data for electromagnetic samples, thereby reducing the difficulty of sample construction. The introduction of TL further improves the sample utilization and optimizes efficiency in electromagnetic tasks. The proposed method enables the rapid and high-degree-of-freedom optimization of antennas. To validate its effectiveness, a reflectarray antenna design incorporating distinct elements is employed as a case study. Simulation results indicate that the designed antenna exhibits a realized gain of 26.3 dBi and aperture efficiency of 46% at the center frequency, and each element has a highly flexible independent structural design. During the optimization process, the proposed hybrid method demonstrates higher optimization efficiency than traditional methods, while significantly reducing sample construction time.

## 1. INTRODUCTION

With the rapid development of wireless communication technology, antennas, as important components of communication systems, are becoming increasingly complex and integrated.

As communication systems become increasingly integrated, antenna design becomes more and more difficult. Traditional antenna design methods rely heavily on the prior design knowledge of designers, who then use parameterized adjustments to achieve the design specifications for the antenna. To finish the numerical optimization of antennas, optimization algorithms play a very important role in these tasks. Genetic algorithms [1, 2], particle swarm algorithms [3–5], and other algorithms have been widely applied in the optimization of antenna parameters [6–8].

However, optimization algorithms inevitably require the evaluation of objective function during operation. In antenna design, the accurate evaluation of objective function requires full-wave simulation, making antenna optimization a very time-consuming process. To solve this problem, many methods have been proposed. Among them, machine learning-based electromagnetic surrogate models have proven to be an effective method [9–13].

Machine learning algorithms have been widely applied in various industries due to their real-time nature and high plasticity. With the widespread application of machine learning in the field of electromagnetic design, the research on establishing electromagnetic surrogate models using machine learning models has become a hot spot. Establishing a real-time alternative model for electromagnetic problems can eliminate the cumbersome full-wave simulation process, making electromagnetic design more efficient.

However, establishing machine learning models for electromagnetic problems is not an easy task. The main challenge at present is the high cost of obtaining electromagnetic training samples. The training of machine learning models requires a large amount of training data. At the same time, in order to ensure the reliability and generalizability of the model, randomly generated training data cannot meet the requirements of machine learning models used for electromagnetic tasks.

In this letter, we proposed a hybrid optimization method combining transfer learning (TL) and self-supervised learning (SSL) to achieve rapid antenna optimization. To achieve high-degree-of-freedom antenna optimization with fewer optimization variables, we used SSL to optimize the antenna pixels. Then, to reduce optimization time, a surrogate model was used to evaluate the objective function during optimization process. To train the surrogate model with a smaller sample construction cost, we used TL based on our trained SSL model. A reflectarray antenna design case is presented. The optimization process shows that the proposed hybrid method demonstrates low sample dependency and high optimization freedom.

## 2. METHODOLOGY

### 2.1. Self-Supervised Learning

Supervised learning (SL) and SSL are two important learning paradigms in machine learning. Unlike SL, SSL directly uses the input data itself as learning information. A typical type of SSL is Autoencoders (AEs). AEs consist of two subnetworks, namely encoder and decoder. The encoder compresses the original high-dimensional input data into a low-dimensional latent

* Corresponding author: Xue-Song Yang (xsyang@uestc.edu.cn).

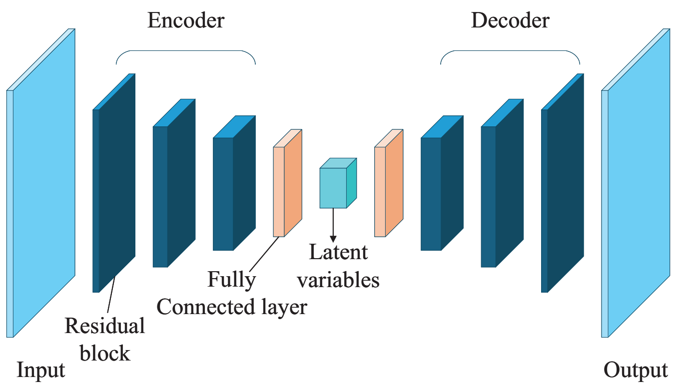


**FIGURE 1**. The schematic diagram of AE.

space, while the decoder reconstructs the original input based on the latent space vector. The schematic diagram of AE is shown in Fig. 1.

The whole training process is self-supervised, and the encoder subnetwork $f_\theta$ establishes a mapping from high-dimensional input data $X$ to a low-dimensional latent space $z$:

$$z = f_\theta(X) \tag{1}$$

where $\theta$ are parameters of the encoder. By the same token, the decoder subnetwork $g_\phi$ establishes the mapping from latent space $z$ to reconstructed data $\bar{X}$:

$$\bar{X} = g_\phi(z) \tag{2}$$

where $\phi$ denotes parameters of the decoder.

The loss function of AE can be defined as reconstruction error, which is calculated using Mean Squared Error (MSE):

$$L(X, \bar{X}) = MSE(X, \bar{X}) \tag{3}$$

so the training objective is to find suitable parameters $(\theta, \phi)$ that minimize the loss function.

Since the entire AE network only uses the input data itself as the label data for training, there is no need for additional annotation of the input data. In other words, using AE for electromagnetic tasks can save a significant amount of sample construction time for full-wave simulation.

## 2.2. Transfer Learning

TL is a machine learning paradigm that aims to transfer knowledge acquired in an existing task to a new task to improve the learning efficiency and performance of the new task. The core idea is to reduce the target domain's dependence on a large amount of labeled data and computational resources by reusing existing knowledge.

In this letter, we use the encoder subnetwork from a pre-trained AE network. The parameters of the encoder's convolutional layer are retained in order to inherit its existing feature extraction capabilities, while the fully connected output layer is redefined to accommodate the new mapping relationship. For each new design task, transfer learning requires retraining to establish new mapping relationships. The diagram of TL is shown in Fig. 2.

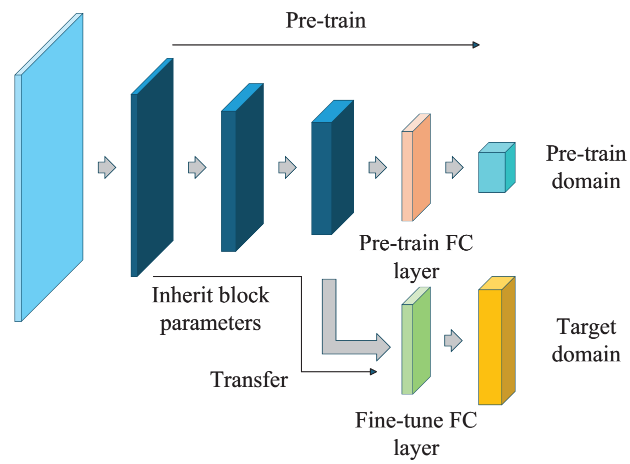


**FIGURE 2**. The schematic diagram of transfer learning.

## 2.3. Optimization Process

In order to achieve high-degree-of-freedom optimization, we use genetic algorithms to optimize latent variables. Latent variables, as intermediate process variables in AE training, can be considered as the results obtained by the encoder when it extracts features from the input data. Latent variables can be restored to their unique corresponding reconstructed outputs through the decoder. In other words, changes in the values of latent variables will cause changes in the corresponding reconstructed outputs. The schematic diagram illustrating the optimization of latent variables is shown in Fig. 3.

Considering that genetic algorithm (GA) requires multiple evaluations of the objective function during operation, using full-wave simulation would be extremely time-consuming. We therefore use TL to fine-tune the encoder of the autoencoder, enabling it to participate in the optimization process as a surrogate model and reducing optimization time. The optimization flowchart is shown in Fig. 4.

## 2.4. Sample Construction

In order to train SSL models and apply TL to train surrogate models, a dataset containing 40,000 shape pattern samples was constructed. The shapes and patterns are created by symmetrical rotation and combination of simple basic patterns, as shown in Fig. 5.

The SSL model was trained using this dataset, and the trained encoder and decoder acquired feature extraction and feature restoration capabilities, respectively. To train the surrogate model, 400 typical patterns were selected, and their electromagnetic label information was obtained through full-wave simulation. To enable rapid electromagnetic label information collection of selected patterns, Python-CST co-simulation is employed. The structure corresponding to the selected pattern will be constructed pixel-by-pixel within Computer Simulation Technology (CST) software according to its pattern matrix via Python scripts. Full-wave simulation of the constructed electromagnetic structure was then performed to obtain its electromagnetic parameters, thereby completing the electromagnetic information labeling of training samples.

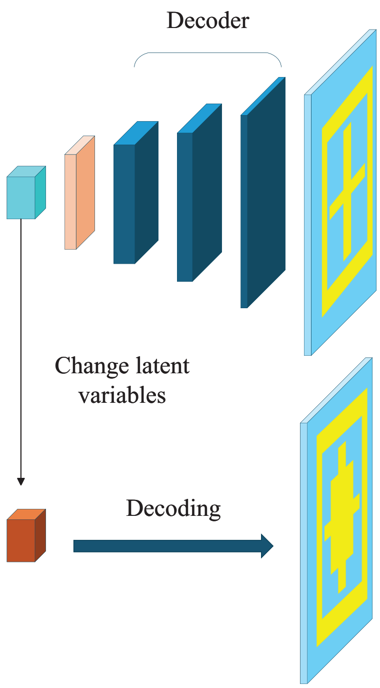


**FIGURE 3**. The schematic diagram illustrating the optimization of latent variables.

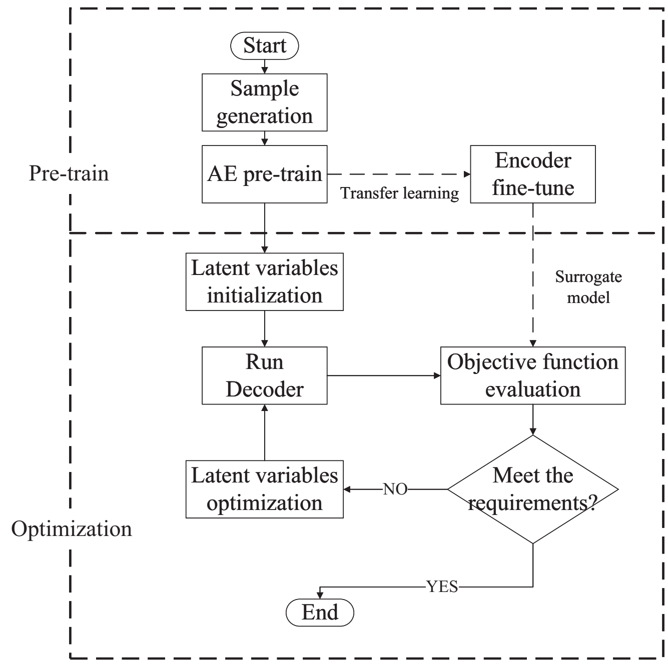


**FIGURE 4**. The schematic diagram of transfer learning.

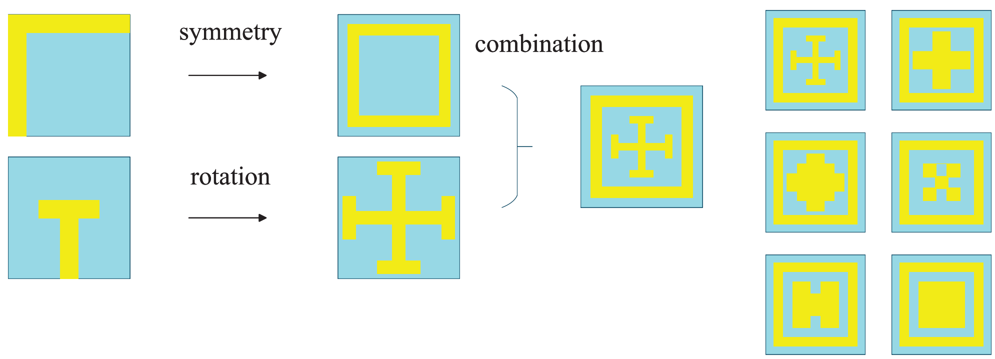


**FIGURE 5**. The training sample construction.

Based on the trained encoder, TL was applied, and the surrogate model was trained using 400 electromagnetic samples with electromagnetic labeled information.

## 3. DESIGN EXAMPLE

A reflectarray antenna design example is presented to verify the effectiveness of the proposed method.

In the design of reflectarray, the design of phase element is crucial. In order to ensure the effectiveness of beam control, the phase element needs to have 360-degree full reflection phase coverage. The traditional design method is to design a unit structure and achieve phase adjustment by adjusting geometric dimensions of the unit structure. The advantage of this design method is that only one unit needs to be designed, and phase control can be easily achieved by changing parameters, while the disadvantage is that the initial unit design directly affects the performance of the entire array. At the same time, significant changes in unit size exacerbate the error between simulation and reality under periodic boundary conditions.

### 3.1. Reflectarray Design

The element is designed using a substrate with the thickness of $t = 0.8$ mm and dielectric constant of $\epsilon_r = 2.55$. The reflectarray is fed by a Ku-band horn antenna, and the ratio of the feed focal length $F$ to the antenna aperture diameter $D$ is set to $F/D = 1.0$. The element design of the reflectarray is shown in Fig. 6.

For multi-layer structures or more complex designs, AE can output each layer's structure separately without retraining. TL training requires collecting samples from multi-layer structures, thus taking more time.

### 3.2. Results and Discussion

All simulation data are generated using CST Studio Suite, and all simulations are conducted on a Microsoft Windows server

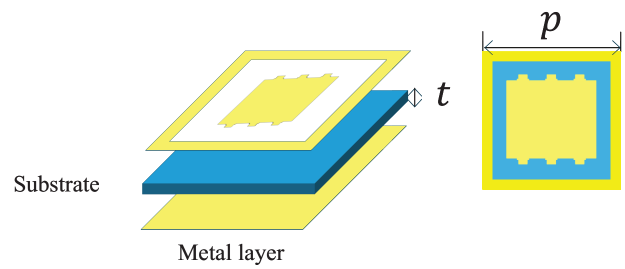


**FIGURE 6.** The reflectarray antenna element. $p = 10\,\text{mm}$, $t = 0.8\,\text{mm}$.

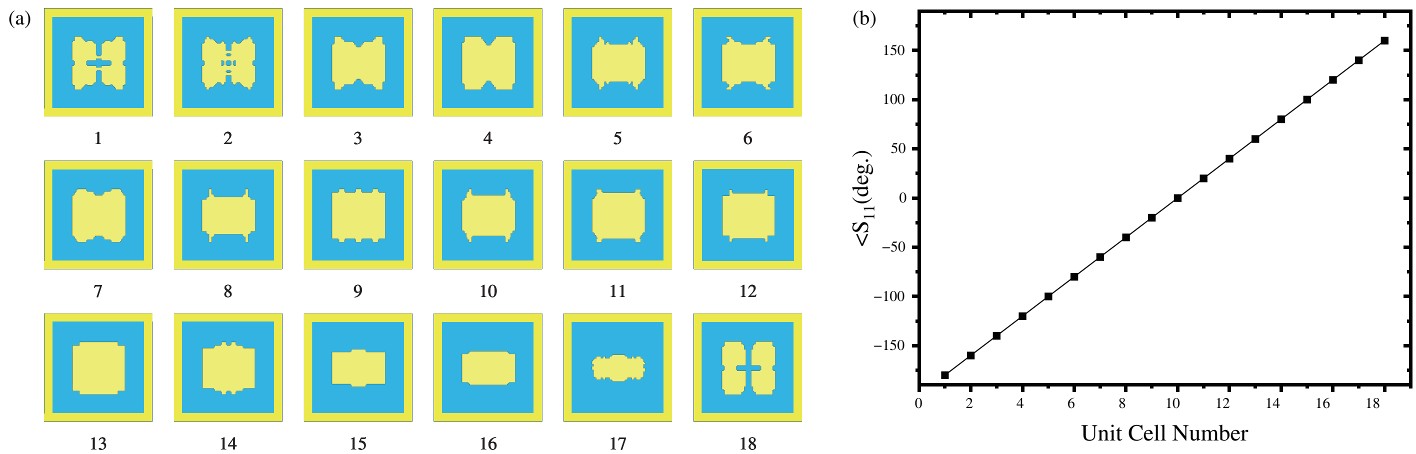


**FIGURE 7.** The optimized elements. (a) Element structures; (b) The phase at 14 GHz.

**TABLE 1.** Optimization method comparison.

| | | Parameter sweep | Parameter + GA | Pixel + GA | This work |
|---|---|---|---|---|---|
| Phase range | | 300 deg. | 300 deg. | 360 deg. | 360 deg. |
| No. of iterations | | 100 | 193 | Est. 7000+ | 486 |
| Time | Train | 0 | 0 | 0 | 11 h |
| | Opt. | 0.8 h | 1.8 h | Est. 100 h+ | 4.5 h |

equipped with $2 \times 3.10$ GHz Intel Xeon Gold 6248R CPUs, $2\times$ Tesla P100-PCIE-16GB GPUs and 1024 GB of RAM.

The element structure of the reflectarray antenna is designed using the proposed optimization method. Rather than using a uniform element structure, we optimized the phase elements every ten degrees. Some of the elements are shown in Fig. 7.

Compared to using individual rectangular patches, the introduction of SSL significantly expands optimization freedom, thereby obtaining greater phase control capabilities than parameter optimization alone. Compared to using GA for pixel optimization, the proposed method achieves higher optimization efficiency. The comparison with traditional optimization methods is shown in Table 1.

The surface of the designed reflectarray is shown in Fig. 8. The phase distribution map is calculated based on the optical path difference at 14 GHz frequency point. In this design case, the optimization objective is the reflection phase at a single frequency point. For broadband optimization tasks, the derivative of the phase at the frequency point can be incorporated as part of the objective function to achieve broadband performance.

The designed reflectarray is simulated. The realized gain at 14 GHz is 26.3 dBi, which is 46% aperture efficiency. The simulation result is shown in Fig. 9. The optimized reflectarray antenna is compared with a uniform rectangular patch reflectarray antenna under the same phase distribution. The reflectarray designed with optimized elements exhibits higher gain performance and lower side-lobe level than the reflectarray using only rectangular patches. This phenomenon arises because optimized elements achieve precise phase compensation while maintaining relatively stable element dimensions across phase variations, resulting in reduced simulation errors under periodic boundary conditions. In contrast, single rectangular patch elements achieve phase compensation by altering their geometric dimensions, introducing greater phase errors.

The trained surrogate model is validated, some element structure is used to verify the accuracy of the model, as shown in Fig. 10.

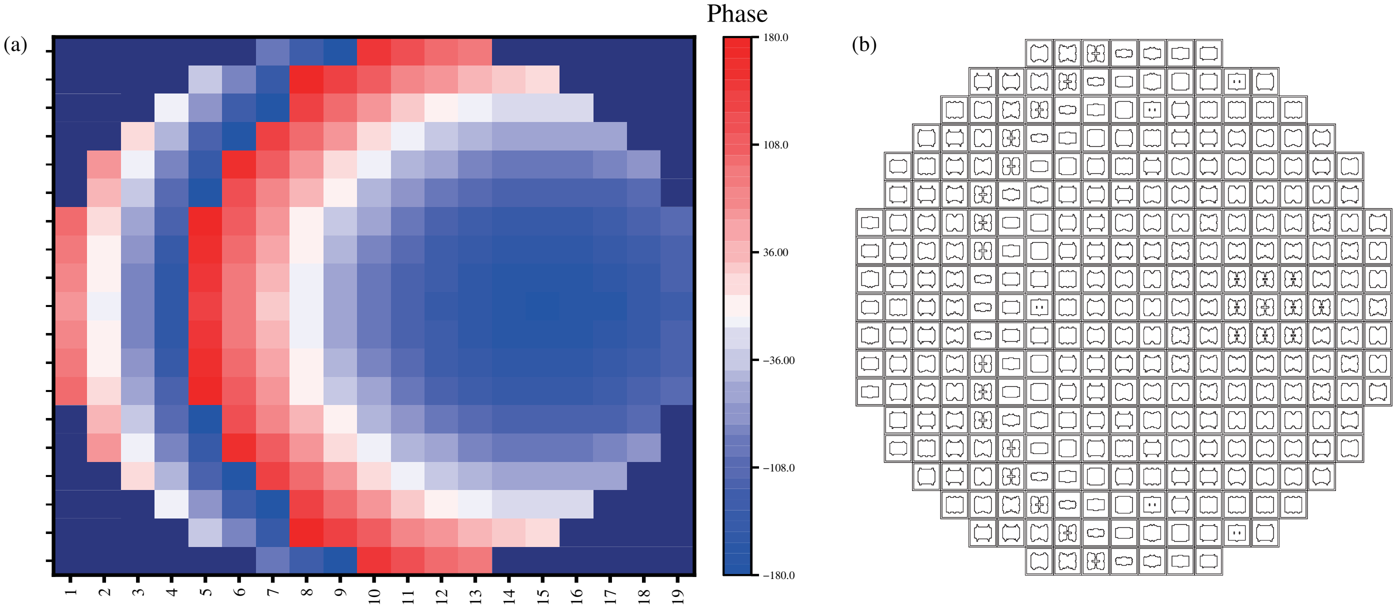


**FIGURE 8**. The designed reflectarray. (a) The calculated phase map at 14 GHz; (b) The designed reflectarrat surface.

**TABLE 2**. Model training information.

| | SL | SSL | TL | |
|---|---|---|---|---|
| | | | Pre-train | Fine-tune |
| No. of training samples | 40 000 | 40 000 | 40 000 | 400 |
| Sample construction time | Est. 1000 h + | 30 min. | 15 min. | 22 h |
| Training time | Est. 10 h + | 8 h | 8 h | 3 h |

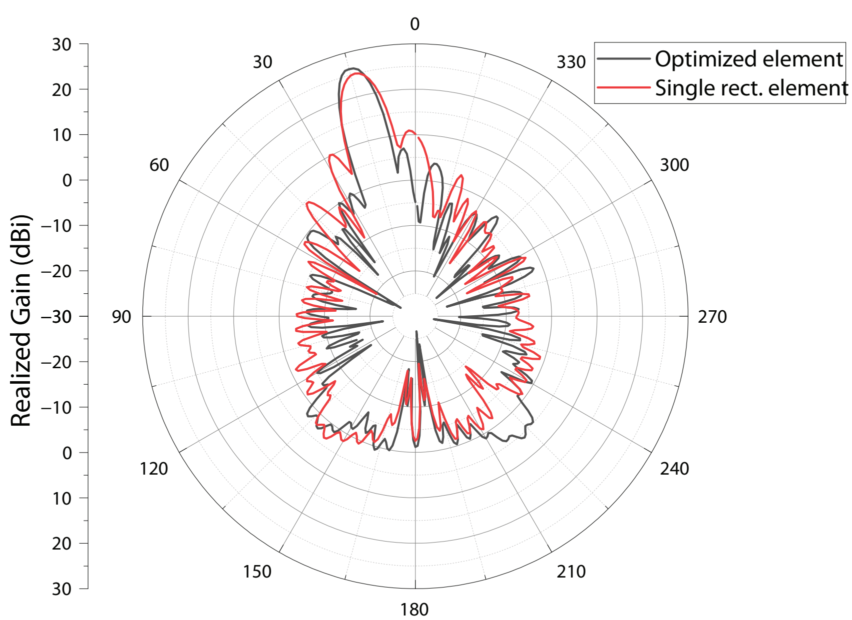


**FIGURE 9**. The radiation pattern of reflectarray at 14GHz. The black curve represents the optimized element, while the red curve represents the single rectangular patch element.

The proposed method constructs a large-scale training dataset at a lower computational cost, ensuring the model's feature extraction capability and generalization ability, thereby guaranteeing the reliability of optimized structures for complex geometries. The detailed information is shown in Table 2.

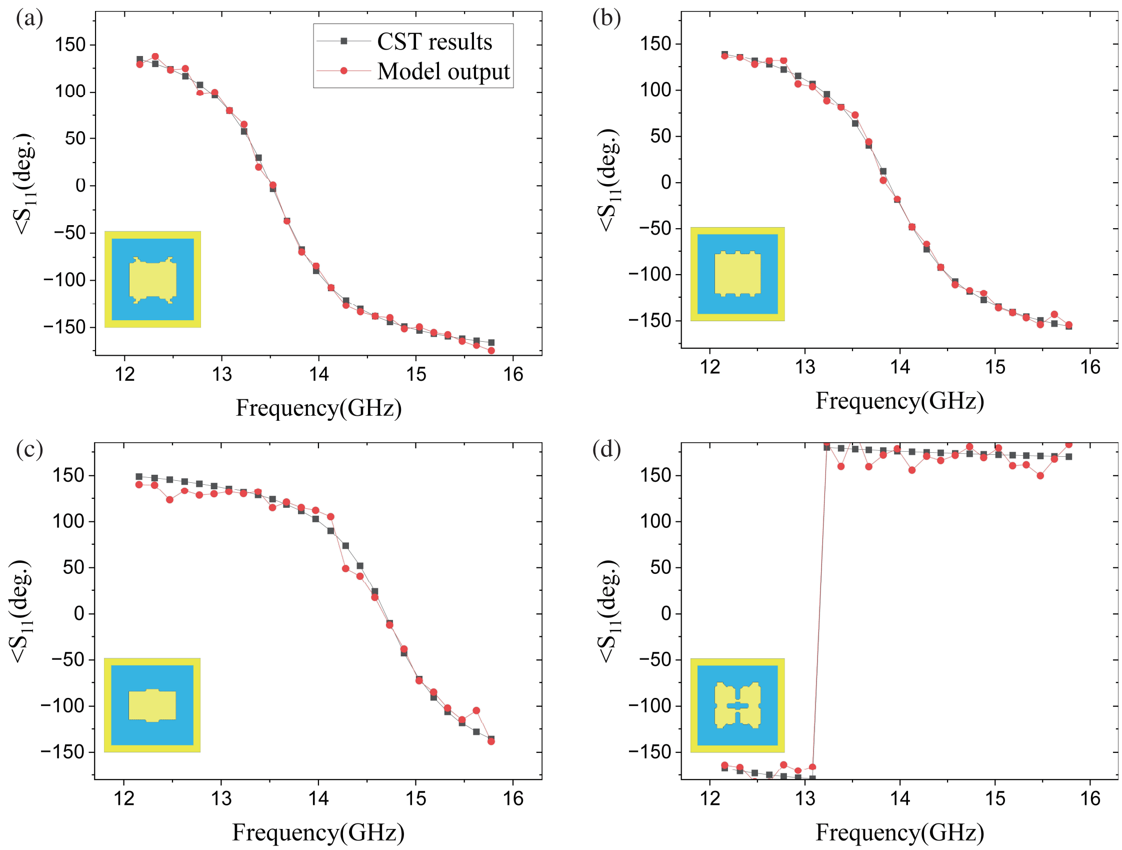


**FIGURE 10**. The results of surrogate model. (a) No. 6 unit cell (−100 degree); (b) No. 9 unit cell (−10 degree); (c) No. 16 unit cell (100 degree); (d) No. 18 unit cell (180 degree).

**TABLE 3**. Literature comparison.

| References | Types of neural networks | Number of samples | Number of simulations | Optimization freedom | Processing time | | |
|---|---|---|---|---|---|---|---|
| | | | | | Sample collection | Model training | Opitmization |
| [14] | VAE | 2400 | 2400 | Pixel-based | Not Given | | |
| [15] | CNN | 20 000 | 20 000+ | Pixel-based | Not Given | | |
| [16] | VAE | 17 500 | 442 | Pixel-based | 340 h | Not Given | Not Given |
| [17] | VAE | 400 | 400 | Parameter-based | 22 h | 8 h | 0.5 h |
| [18] | CGAN | 5 000+ | 5 000+ | Pixel-based | Not Given | | |
| This work | AE | 40 000 | 400 | Pixel-based | 0.5h | 11 h | 1.3 h |

Compared with traditional supervised learning methods of directly training machine learning electromagnetic surrogate models, the proposed method significantly reduces sample collection time. As an optimization method, it also demonstrates great optimization flexibility, providing conditions for the optimization of various types of antennas. The proposed method is also compared with machine-learning based optimization methods, as listed in Table 3.

## 4. CONCLUSION

In this letter, we proposed a hybrid optimization method combining SSL and TL. The introduction of SSL has provided conditions for high-degree-of-freedom antenna optimization, while significantly reducing the cost of obtaining training samples. To further improve sample utilization and optimize efficiency, a surrogate model was trained using TL and used to rapidly evaluate the objective function in the optimization process. A reflectarray antenna design case is presented. The simulation results show that the optimized antenna achieves 26.3 dBi realized gain by using nonuniform phase elements. The proposed hybrid method demonstrates low electromagnetic sample dependency and high optimization freedom, and it can play an important role in the design of various types of electromagnetic structures.

## ACKNOWLEDGEMENT

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## REFERENCES

[1] Rocca, P., R. J. Mailloux, and G. Toso, "GA-based optimization of irregular subarray layouts for wideband phased arrays design," *IEEE Antennas and Wireless Propagation Letters*, Vol. 14, 131–134, 2015.

[2] Xiong, J., W.-Q. Wang, H. Shao, and H. Chen, "Frequency diverse array transmit beampattern optimization with genetic algorithm," *IEEE Antennas and Wireless Propagation Letters*, Vol. 16, 469–472, 2016.

[3] Robinson, J. and Y. Rahmat-Samii, "Particle swarm optimization in electromagnetics," *IEEE Transactions on Antennas and Propagation*, Vol. 52, No. 2, 397–407, 2004.

[4] Poli, L., P. Rocca, L. Manica, and A. Massa, "Handling sideband radiations in time-modulated arrays through particle swarm optimization," *IEEE Transactions on Antennas and Propagation*, Vol. 58, No. 4, 1408–1411, 2010.

[5] Zhang, S.-R., Y.-X. Zhang, and C.-Y. Cui, "Efficient multiobjective optimization of time-modulated array using a hybrid particle swarm algorithm with convex programming," *IEEE Antennas and Wireless Propagation Letters*, Vol. 19, No. 11, 1842–1846, 2020.

[6] Quevedo-Teruel, O. and E. Rajo-Iglesias, "Ant colony optimization in thinned array synthesis with minimum sidelobe level," *IEEE Antennas and Wireless Propagation Letters*, Vol. 5, 349–352, 2006.

[7] Gregory, M. D., Z. Bayraktar, and D. H. Werner, "Fast optimization of electromagnetic design problems using the covariance matrix adaptation evolutionary strategy," *IEEE Transactions on Antennas and Propagation*, Vol. 59, No. 4, 1275–1285, 2011.

[8] Wang, J., X.-S. Yang, X. Ding, and B.-Z. Wang, "Antenna radiation characteristics optimization by a hybrid topological method," *IEEE Transactions on Antennas and Propagation*, Vol. 65, No. 6, 2843–2854, 2017.

[9] Wang, Z., S. Fang, Q. Wang, and H. Liu, "An ANN-based synthesis model for the single-feed circularly-polarized square microstrip antenna with truncated corners," *IEEE Transactions on Antennas and Propagation*, Vol. 60, No. 12, 5989–5992, 2012.

[10] Xiao, L.-Y., W. Shao, Z.-X. Yao, and S. Gao, "Data mining techniques in artificial neural network for UWB antenna design," *Radioengineering*, Vol. 27, No. 1, 70–78, 2018.

[11] Xiao, L.-Y., W. Shao, F.-L. Jin, and B.-Z. Wang, "Multiparameter modeling with ANN for antenna design," *IEEE Transactions on Antennas and Propagation*, Vol. 66, No. 7, 3718–3723, 2018.

[12] Feng, F., C. Zhang, J. Ma, and Q.-J. Zhang, "Parametric modeling of EM behavior of microwave components using combined neural networks and pole-residue-based transfer functions," *IEEE Transactions on Microwave Theory and Techniques*, Vol. 64, No. 1, 60–77, 2016.

[13] Liu, Y.-F., L. Peng, and W. Shao, "An efficient knowledge-based artificial neural network for the design of circularly polarized 3-D-printed lens antenna," *IEEE Transactions on Antennas and Propagation*, Vol. 70, No. 7, 5007–5014, 2022.

[14] You, X. C. and F. H. Lin, "Inverse design of reflective metasurface antennas using deep learning from small-scale statistically random pico-cells," *Microwave and Optical Technology Letters*, Vol. 66, No. 2, e34068, 2024.

[15] Zhu, R., T. Qiu, J. Wang, S. Sui, C. Hao, T. Liu, Y. Li, M. Feng, A. Zhang, C.-W. Qiu, and S. Qu, "Phase-to-pattern inverse design paradigm for fast realization of functional metasurfaces via transfer learning," *Nature Communications*, Vol. 12, No. 1, 2974, 2021.

[16] Naseri, P. and S. V. Hum, "A generative machine learning-based approach for inverse design of multilayer metasurfaces," *IEEE Transactions on Antennas and Propagation*, Vol. 69, No. 9, 5725–5739, 2021.

[17] Wei, Z., Z. Zhou, P. Wang, J. Ren, Y. Yin, G. F. Pedersen, and M. Shen, "Equivalent circuit theory-assisted deep learning for accelerated generative design of metasurfaces," *IEEE Transactions on Antennas and Propagation*, Vol. 70, No. 7, 5120–5129, 2022.

[18] Lyu, Y., T. H. Gan, and Z. N. Chen, "TE-TM balanced wide-angle metacells for low scan-loss metalens antenna using prior knowledge-guided generative deep learning-enabled method," *IEEE Transactions on Antennas and Propagation*, Vol. 73, No. 5, 2940–2949, 2025.