Surrogate Model Assisted Frequency Selective Surfaces Multifunctional Optimization

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***Abstract*—In this paper, we presented a novel differential evolution (DE)-based optimization approach for accelerating the iterative design process of frequency selective surfaces (FSS). By integrating a Bayesian neural network (BNN) and lower confidence bound (LCB) prescreening methods, our approach constructs a simulation surrogate model that effectively leverages a priori knowledge from equivalent circuits. This method is well-suited for optimizing multifunctional filtering FSS designs using the same design prototype. The proposed algorithm's performance was validated through a typical case study, demonstrating its effectiveness in enhancing the optimization process. The realization details and code are available for further exploration.**

https://github.com/LeeHongji/FSS_auto_optimization.git

Keywords—FSS optimization, Bayesian neural network (BNN), differential evolution (DE), lower confidence bound (LCB), surrogate modeling.

I. Introduction

Frequency Selective Surfaces (FSSs) are widely used in applications such as absorbers, antennas, and radomes due to their ability to filter electromagnetic waves through periodic resonant unit designs [1]. Traditional evolutionary algorithms like genetic algorithms, particle swarm optimization, and differential evolution (DE) have been applied to FSS design but face challenges with computation speed and accuracy [2]. Recently, deep learning approaches have been used to optimize FSS designs, although they require large datasets and result in high computational costs [3]. This paper introduces a surrogate-model-assisted DE approach for multifunctional FSS design, aiming to enhance convergence speed and accuracy. Key innovations include an equivalent-circuit-guided Bayesian neural network (BNN) for surrogate modeling, a lower confidence bound (LCB) method for selecting the best design, modified DE operators, and a new objective function tailored for FSS optimization [4].

II. Algorithm

A. Overall Algorithm Framework

The overall optimization process is shown in Fig.1, we use DE as the basic optimization algorithm in this design and use knowledge-guided BNN as the simulation surrogate model to find the locally optimal candidate. The algorithm works as follows:

Step 1: Set the optimization objectives for S-parameters based on demand.

Step 2: Build up the equivalent circuit for the problem based on the optimization objectives

Step 3: Select the appropriate pattern of the FSS and build up the 3D simulation model according to the equivalent circuit.

Step 4: Sample α candidate designs from the design space $[\boldsymbol{LB}, \boldsymbol{UB}]^d$ ($\boldsymbol{LB}$ and $\boldsymbol{UB}$ are the lower and upper bounds of design variables, respectively) using constrained Latin hypercube sampling method, the constrained set as $h(\boldsymbol{x})$. Carry out EM simulations to obtain their performance values using CST and form the initial database.

Step 5: If a preset stopping criterion is met (e.g., the computing budget is exhausted or satisfies the specifications), output the best candidate design from the database; otherwise, go to Step 6.

Step 6: Obtain the N best candidate designs from the database to form a population $\boldsymbol{P}$.

Step 7: Apply the modified DE mutation operator and crossover operator to $\boldsymbol{P}$ to create N new child solutions.

Step 8: For each child solution, obtain τ nearest samples (based on the Euclidean distance) as the training data points and construct a BNN-based surrogate model.

Step 9: Prescreen the child solutions generated in Step 7 using the BNN model predictions and the LCB method.

Step 10: Carry out EM simulation to the estimated best child solution from Step 9. Add this evaluated candidate design and its performance values to the database. Go back to Step 5.

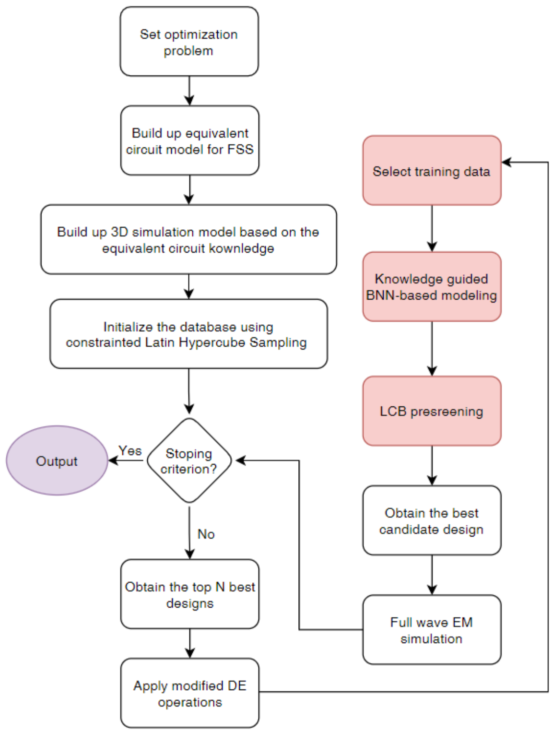

Fig. 1. The overall framework of the proposed optimization algorithm.

III. Implementation

A. Experimental Example

Fig. 2 illustrates the schematic diagram of the FSS. Such a prototype structure could realize a multifunctional filtering ability, including a single passband, double passband, triple passband, or stopband. We selected such a multilayer prototype FSS to demonstrate the algorithm's optimization ability.

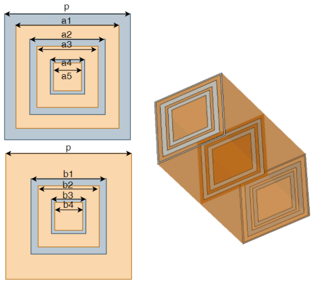

Fig. 2. (a) The top and bottom layer of the FSS (b) The middle layer of the FSS (c) The 3D view of the FSS

Our objective function includes an optimization objective for S11 and an optimization objective for S21, where S11 needs to be lower than -10dB within the frequency band $\boldsymbol{f_{S11}} = (f_1, f_2, \dots, f_l)$, and S21 needs to be lower than -15dB within the frequency band $\boldsymbol{f_{S21}} = (f_1, f_2, \dots, f_k)$. The composition of the objective function is shown below.

$$L_{s11} = max\left(0, \sum_{l} 20log_{10}|S11(f_l)| + 10\right) \quad (1)$$

$$L_{s21} = max\left(0, \sum_{k} 20log_{10}|S21(f_k)| + 15\right) \quad (2)$$

Fig. 2 shows the design parameter set. As seen from the equivalent circuit diagram in Fig. 3(a), three layers of FSS are spaced by dielectric layers. We design the network structure of BNN as shown in Fig. 3(b) based on the prior knowledge.

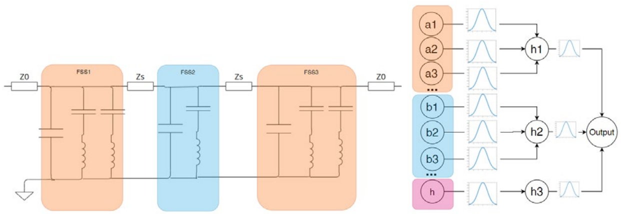

Fig. 3. The equivalent circuit diagram of the FSS and the BNN corresponds to the equivalent circuit diagram

B. Optimization Result

In Fig. 4(a)-(c), the optimization goal is a single passband with targets: S_{11} = [11GHz, 15.5GHz] < -10dB and S_{21} = [17GHz, 20GHz] < -15dB. Starting from the smallest objective function of 500 pre-collected data points (Fig. 4a), the optimization required only 22 iterations to get the result, as shown in Fig. 4(b), significantly reducing EM simulation time. For the multi-band design, targets are S_{11} = [11.5GHz, 13GHz; 18GHz, 19.5GHz] < -10dB and S_{21} = [14.5GHz, 16.5GHz; 21.5GHz, 24GHz] < -15dB. With an initial value in Fig. 4(d), the final result (Fig. 4e) was achieved in 35 iterations, as indicated by the convergence curve in Fig. 4(f), ensuring efficient optimization with minimal simulations.

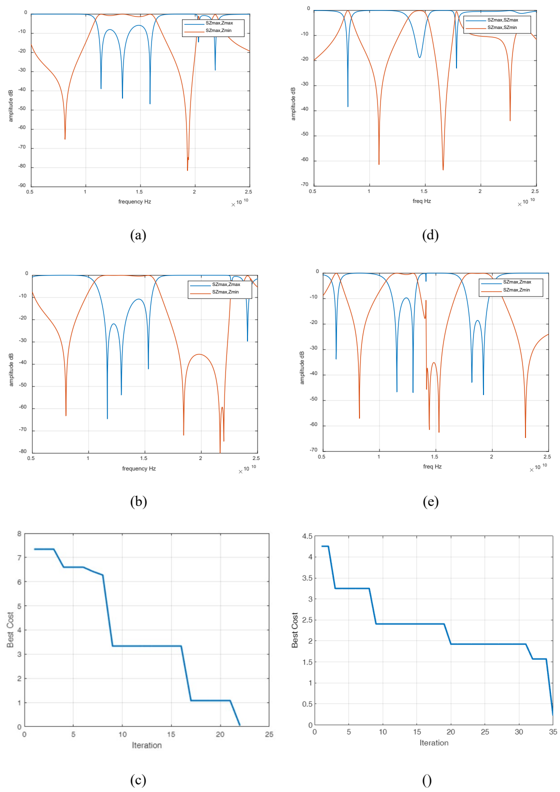

Fig. 4. (a) Initial result of single passband example. (b) Optimization result of single passband example. (c) Iterative convergence curve of the single passband example (d) Initial result of multi-band example. (e) Optimization result of multi-band example. (f) Iterative convergence curve of the single passband example

IV. Conclusion

This paper introduced a differential evolution (DE)-based approach to speed up the design of frequency selective surfaces (FSS). By using a Bayesian neural network (BNN) and lower confidence bound (LCB) prescreening, we built a surrogate model that incorporates knowledge from equivalent circuits. This method is effective for optimizing multifunctional filtering FSS designs. The results demonstrate the efficient optimization performance of the algorithm.

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