A Hybrid Optimization Strategy of Random Forest and Differential Evolution Algorithm for Wideband Antennas

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Abstract – This paper presents a hybrid optimization strategy for wideband antenna design that leverages the strengths of both Random Forest (RF) and Differential Evolution (DE) algorithms. The strategy employs DE for iteratively updating antenna parameters and RF for feature selection in the process of antenna performance optimization. Initially, DE is applied to update antenna parameters for a predetermined number of iterations, generating a dataset of antenna performance metrics. This dataset is then used to train an RF model, which identifies the importance of each design variable. Feature selection, guided by the RF-derived importance, is applied to reduce the dimensionality of the search space. DE subsequently continues the optimization process within this reduced parameter space. Validation of this hybrid approach is performed through the design of a wideband slot antenna and compared against standalone DE, Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Simulated Annealing (SA). Results demonstrate that the proposed strategy significantly accelerates convergence, achieving the target reflection coefficient and gain with substantially fewer iterations than the other methods (reductions of 75.56%, 45%, 42.11%, and 50% compared to DE, GA, SA, and PSO, respectively). Furthermore, the hybrid strategy consistently finds superior solutions exhibiting lower loss values compared to the benchmark algorithms. The method offers a computationally efficient, interpretable, and effective approach to antenna optimization.

Index Terms – Antenna, Differential Evolution (DE) algorithm, feature selection, Random Forest (RF) algorithm.

I. INTRODUCTION

Antenna performance critically impacts wireless communication systems' efficiency and reliability [1]. Traditional design methods rely on High Frequency Structure Simulator (HFSS) or Computer Simulation Technology (CST) simulations and empirical adjustments, requiring iterative parameter tuning and hundreds of electromagnetic simulations for optimization a time-intensive process [2]. With emerging technologies like antenna arrays [3, 4] and broadband circularly polarized antennas [5, 6] increasing design complexity, conventional approaches face limitations. This underscores the urgent need for automated optimization methods to enhance design efficiency and address modern performance demands.

Meta-heuristic algorithms, inspired by natural phenomena and physical processes, have gained prominence in AI-driven optimization. These methods fall into four categories: evolutionary (e.g., DE [7], Genetic Algorithm (GA) [8]), swarm-based (e.g., Particle Swarm Optimization (PSO) [9]), human-inspired (e.g., Teaching-Learning-Based Optimization, TLBO [10]), and physics- or chemistry-based (e.g., Simulated Annealing (SA) [11]). While they enhance antenna design accuracy and efficiency, their reliance on thousands of simulation iterations to approach global optima still results in prolonged optimization cycles, limiting time-sensitive applications.

Advances in computing power have driven machine learning (ML) integration in antenna optimization, with approaches like Artificial Neural Network (ANN)-based multi-fidelity modeling [12], Random Forest (RF)-augmented models [13], Support Vector Machine (SVM)-Gaussian hybrids [14] serving as surrogate models and Convolutional Neural Networks (CNN)-aided Reinforcement Learning (RL) [15]. While these surrogates accelerate electromagnetic simulation predictions, they face challenges: limited generalization across environmental conditions and dependence on time-intensive electromagnetic simulation datasets for training [2].

This paper presents a hybrid optimization method for wideband antenna design using RF and Differential Evolution (DE) algorithms. DE generates a dataset by iteratively updating antenna parameters for RF model training. The RF model assesses each design variable's importance for feature selection to reduce search space dimensionality, after which DE optimizes within this

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reduced space. Validation via wideband slot antenna design shows this hybrid method significantly reduces iterations compared to standalone DE, GA, PSO, and SA, and consistently finds better solutions with lower loss. It offers a computationally efficient, interpretable, and effective antenna optimization solution.

The remainder of this paper is organized as follows. Section II introduces DE and RF fundamentals. Section III details the hybrid strategy. Section IV presents a case study, followed by conclusions in section V.

II. FUNDAMENTAL ALGORITHM

A. Random Forest

RF is an ensemble learning method utilizing decision trees with Bagging integration and randomized training [16]. Each tree is trained on distinct data subsets, reducing errors through complementary predictions. Key advantages include high accuracy, robustness, overfitting resistance, and feature importance analysis for high-dimensional data. As shown in Fig. 1, RF aggregates results from multiple trees: classification uses majority voting, while regression employs averaging, ensuring reliable predictions across diverse tasks.

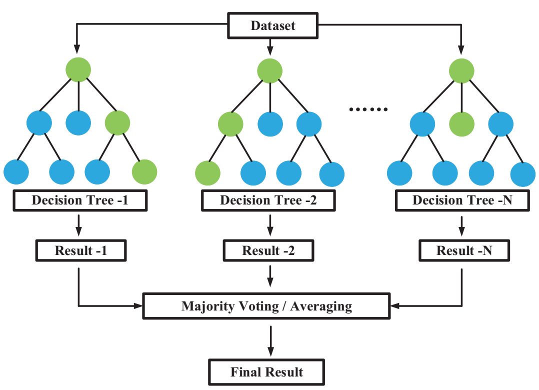


Fig. 1. Workflow of Random Forest.

B. Differential Evolution algorithm

The DE algorithm is a population-based optimization method inspired by natural evolution, employing mutation, crossover, and selection operations to iteratively refine solutions [17]. As shown in Fig. 2, DE initializes a population and iteratively updates it through differential mutation, crossover, and competitive selection until convergence. Its strengths lie in differential vector-driven global exploration, gradient-free optimization for non-differentiable functions, and robustness in escaping local optima within high-dimensional spaces. These attributes, combined with inherent parallelism, make DE particularly effective for complex electromagnetic design problems requiring broad search capabilities and adaptability.

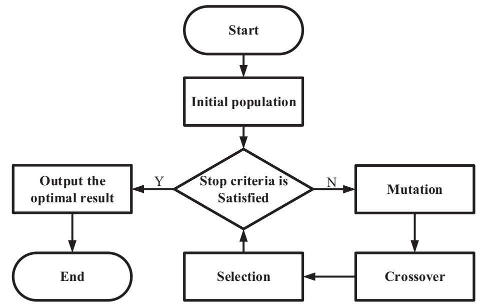


Fig. 2. Workflow of Differential Evolution algorithm.

III. HYBRID OPTIMIZATION STRATEGY

The workflow of the hybrid optimization strategy is illustrated in Fig. 3, and the corresponding pseudocode is presented in Table 1. The specific steps of the algorithm are as follows.

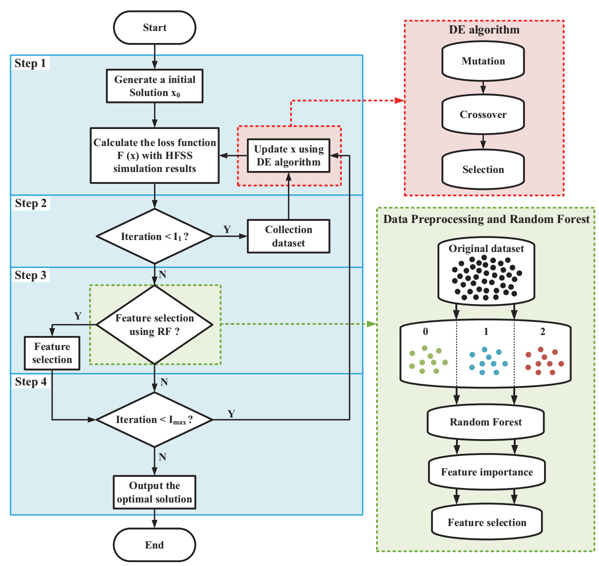


Fig. 3. Workflow of hybrid optimization strategy.

Step 1: Initialization is performed. The initial target x_0, representing the initial values of the antenna optimization variables, is input into HFSS for simulation. The loss function $F(x_0)$ is calculated to obtain the loss value, after which the process proceeds to Step 2.

Step 2: If the iteration count has not reached I_1, store the HFSS simulation data and use the DE algorithm to update the antenna variables through mutation, crossover, and selection, then simulate in HFSS to calculate $F(x)$ and return to Step 2. The process of updating the antenna variables, as shown in the red block diagram in Fig. 1. If the iteration count reaches I_1, then proceed to Step 3.

Step 3: If feature selection using RF is enabled, the dataset from Step 2 is preprocessed and classified into

Table 1: Pseudo-code of the proposed hybrid optimization strategy

Algorithm: Hybrid Optimization strategy for Antenna Design

```
begin
initialize x = x_0, x_space, I_max, I_1 and dataset D
for i = 1 to I_max do
  if i < I_1 then
    simulate x in HFSS, calculate loss F(x)
    store (x, S_11(x)) in D
    update x using DE algorithm
  else
    if feature selection is enabled then
      preprocess D (classify into 0,1,2)
      train RF model, perform feature selection
      update x_space with feature selection
    end
    update x using DE algorithm
    simulate x in HFSS, calculate loss F(x)
  end
end
output optimal solution
end
```

0 (bad), 1 (medium), and 2 (good). This classified data is used to train the RF, obtaining feature importance for selection. The process of data preprocessing and RF is shown in the green block diagram in Fig. 1. If not enabled, this step is skipped. (It should be noted that when the dimensions of the antenna are high, Step 3 can be activated multiple times during the algorithm execution process for multiple rounds of feature selection.)

Step 4: If the maximum preset iteration count I_{max} has not been reached, use the DE algorithm to update the antenna optimization variables, calculate the loss function $F(x)$, and return to Step 2. If I_{max} is reached, output the optimal solution and the process is terminated.

IV. CASE STUDY

This section analyzes antenna optimization simulations using hybrid optimization strategies and four benchwork algorithms. The experiment has a preset maximum of 100 iterations ($I_{max} = 100$) and 20 data collection iterations ($I_1 = 20$). Each generation's population size is 10, and a loss value of -60 is acceptable. The hybrid optimization strategy runs three times, with Step 3 performed once per execution due to the antenna's low number of optimization variables.

A. Structure of the wideband slot antenna

The structure, variables, and boundaries of the wideband slot antenna are shown in Fig. 4. The antenna is used to verify the effectiveness of the hybrid optimization strategy [18]. The antenna uses an FR4 substrate with a relative permittivity of 4.4, a loss tangent of 0.02, and a thickness of 1.6 mm. The design involves a square slot on one side of the substrate and a small branch within the slot. To highlight the hybrid strategy's benefits, minor antenna modifications are introduced, expanding the search space by one dimension.

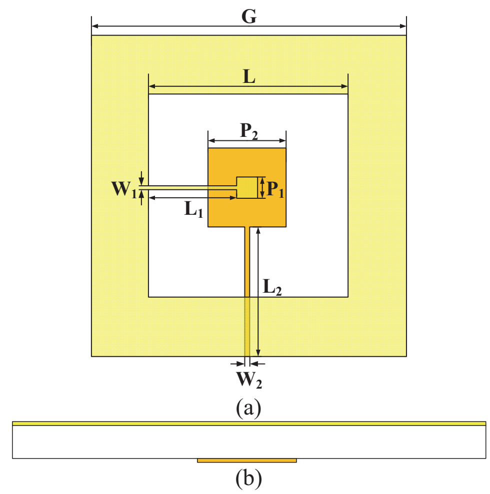


Fig. 4. Wideband slot antenna: (a) perspective and (b) side view.

B. Settings before optimization

Table 2 presents the optimization variables for the antenna, detailing each parameter's search space. The algorithm operates within an 8-dimensional search space. Additionally, two optimization objectives have been established for the antenna. The first objective concerns the antenna reflection coefficient, which must be below -10.0 dB between 1.5 GHz and 4.2 GHz, with a particular emphasis on maintaining an average below -15 dB throughout the entire operating band. The second objective pertains to the antenna gain, requiring an average exceeding 3.8 dB within the operational frequency range.

Table 2: Optimization variable of wideband slot antenna (unit: mm)

Variable	Boundary
$\boldsymbol{G}$	$[75.0, 85.0]$
$\boldsymbol{L}$	$[44.0, 64.0]$
$\boldsymbol{L}_1$	$[10.0, 30.0]$
$\boldsymbol{L}_2$	$[14.0, 45.0]$
$\boldsymbol{W}_1$	$[0.5, 1.5]$
$\boldsymbol{W}_2$	$[0.5, 1.5]$
$\boldsymbol{P}_1$	$[4.0, 10.0]$
$\boldsymbol{P}_2$	$[16.0, 22.0]$

This optimization involves two inherently coupled performance metrics: S_{11} and Gain. To ensure balanced consideration of both objectives without excessively prioritizing one at the expense of the other, a product-form loss function is employed. To address these requirements, this paper introduces a loss function $F(x)$, as defined in equation (1):

$$F(x) = \omega f_1(x) \times f_2(x), \tag{1}$$

where $x = [G, L, L_1, L_2, W_1, W_2, P_1, P_2]$ is the value of the optimization variable, ω is the weight coefficient, $f_1(x)$ is the function of the optimization objective 1, $f_2(x)$ is the function of the optimization objective 2. The details of $f_1(x)$ and $f_2(x)$ are shown in equations (2) and (3) respectively:

$$f_1(x) = \begin{cases} avg(S_{11}(x) \mid S_{11} < -10\,dB, \\ \qquad f \in [1.5,\ 4.2]), & \text{(I)} \\ avg(S_{11}(x) \mid S_{11} < -10\,dB, \\ \qquad f \notin [1.5,\ 4.2]), & \text{(II)} \\ min(S_{11}(x) \mid S_{11} > -10\,dB), & \text{(III)} \end{cases} \tag{2}$$

$$f_2(x) = avg(Gain(x) \mid f_1(x)) \tag{3}$$

where condition (I) requires that under the optimization variable x, the value of S_{11} in the frequency range [1.5, 4.2] GHz from EM simulation must be less than -10 dB. Here, $f_1(x)$ is defined as the average value of S_{11} below -10 dB, with a weight coefficient ω set to 1. Condition (II) specifies that under the optimization variable x, the value of S_{11} outside the frequency range [1.5, 4.2] GHz from EM simulation must be less than -10 dB. In this case, $f_1(x)$ is also the average value of S_{11} below 10 dB, but the weight coefficient ω is set to 0.5. Condition (III) encompasses all other conditions not covered by Conditions (I) and (II). For this condition, $f_1(x)$ is defined as the minimum value of S_{11}, and the weight coefficient ω is set to 0.1. Equation (3) states that for any condition, $f_2(x)$ is the average gain within the frequency range used by $f_1(x)$ under that same condition. This setting of weight coefficients aims to enhance the loss value for better solutions and worsen it for poorer solutions, thereby improving search efficiency and subsequently boosting the optimization efficiency of the antenna.

C. Feature selection result of slot antenna

Table 3 presents the feature importance, algorithm training accuracy, and feature selection results for the triple hybrid optimization strategy. As indicated by these results, the feature selection for the wideband slot antenna under the three times hybrid optimization strategies are P_2, P_1, and $\{P_1, W_1\}$ for DERF1, DERF2, and DERF3, respectively. These selected features are subsequently removed from the antenna parameters to achieve dimensionality reduction. Through this process, the search space of the antenna is effectively reduced, thereby enhancing the optimization efficiency and speed.

Table 3: Feature importance of hybrid optimization strategy

Feature	DERF1	DERF2	DERF3
G	0.1067	0.0881	0.1117
L	0.1095	0.0990	0.0998
L_1	0.1012	0.0940	0.1105
L_2	0.3134	0.2915	0.2943
W_1	0.1446	0.0928	0.0788
W_2	0.0823	0.1296	0.1312
P_1	0.0808	0.0745	0.0724
P_2	0.0615	0.1305	0.1016
Accuracy	0.9167	0.8667	0.8867
Feature selection	P_2	P_1	P_1, W_1

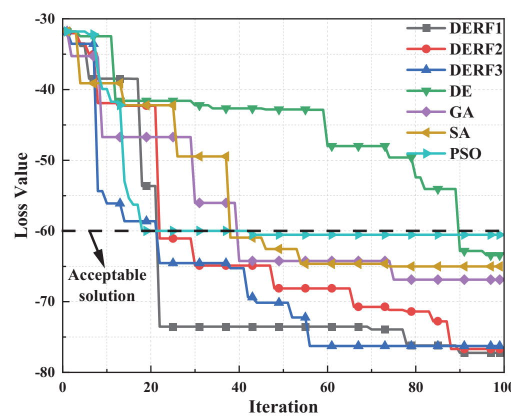
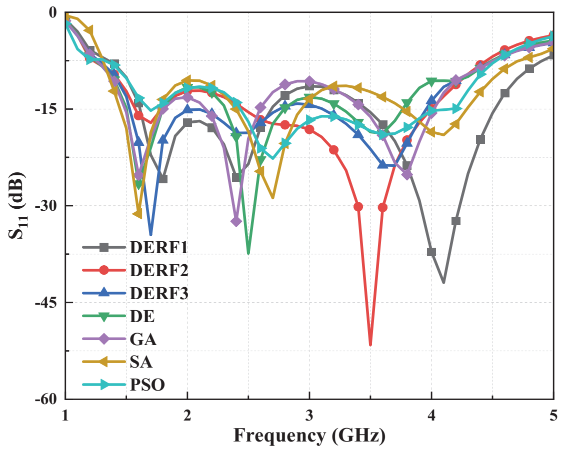


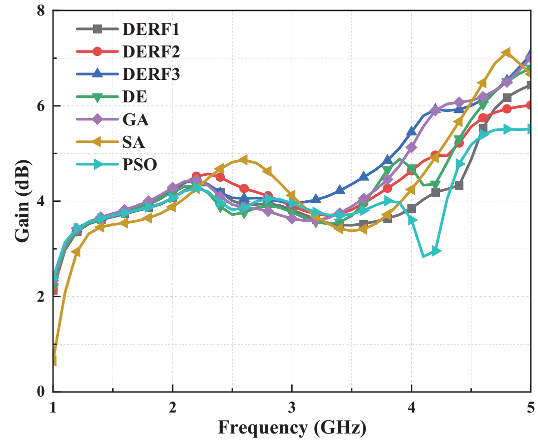
Fig. 5. Loss value with the number of iterations.

D. Results of algorithm comparison

Figure 5 illustrates the comparative iterative loss values for the hybrid optimization strategy and meta-heuristic algorithms. Additionally, Fig. 6 presents the S_{11} and gain graphs for each algorithm. The above simulation results are summarized and analyzed in Table 4. The hybrid strategy converges consistently in three runs, needing 22 iterations to reach the target loss of -60 (with the first 20 for data collection). In comparison, DE, GA, SA, and PSO require 90, 40, 38, and 44 iterations, respectively. The hybrid strategy's loss value exceeds -75, while others reach about -65. Thus, the hybrid optimization strategy reduces iterations for acceptable solutions and finds better solutions in antenna optimization.



(a)



(b)

Fig. 6. Simulation (a) S_{11} and (b) Gain.

Table 4: Performance comparison of each algorithm

Algorithm	F(x)	$\mathbf{F(x) < -60}$	$S_{11} < -10$ dB	Avg ($\mathbf{S_{11}}$)	Avg (Gain)
DERF1	−77.241	22	1.5–4.7 GHz	−19.157	4.032
DERF2	−76.695	22	1.5–4.2 GHz	−18.463	4.154
DERF3	−76.278	22	1.5–4.2 GHz	−17.463	4.368
$\boldsymbol{DE}$[3]	−63.417	90	1.4–4.2 GHz	−15.874	3.995
$\boldsymbol{GA}$[4]	−66.872	40	1.4–4.2 GHz	−16.141	4.143
$\boldsymbol{SA}$[5]	−65.004	38	1.4–4.5 GHz	−15.555	4.179
PSO [7]	−60.528	44	1.5–4.3 GHz	−15.750	3.843

V. CONCLUSION

This paper introduced a hybrid optimization strategy for wideband antenna design, integrating Random Forest (RF) for feature selection with Differential Evolution (DE) for parameter optimization. The DE algorithm generates a dataset of antenna performance metrics, which is then used by RF to rank the importance of each design variable. This ranking enables a dimensionality reduction of the search space through feature selection, significantly accelerating the subsequent DE-driven optimization. The efficacy of this approach was demonstrated through the design of a wideband slot antenna. Comparative studies against standalone DE, GA, PSO, and SA algorithms revealed that the hybrid strategy achieves substantially faster convergence, requiring significantly fewer iterations to reach a target performance level. Moreover, the proposed method consistently discovered higher-quality solutions, as evidenced by lower loss values. The results clearly validate the proposed hybrid DE-RF strategy as a computationally efficient and effective approach for wideband antenna optimization, offering both improved convergence speed and superior solution quality. The interpretability provided by the RF feature importance analysis is an additional advantage, offering insights into the design process.

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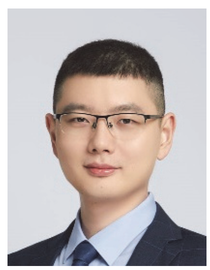

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