

# Accelerated Convergence in GA-Based Patch Antenna Optimization Using Fuzzy Logic and Machine Learning

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**Abstract**— This paper presents an adaptive mutation framework for accelerating the genetic algorithm (GA) convergence in microstrip patch antenna optimization. While the antenna geometry itself is kept simple—a pixelated rectangular patch on an FR4 substrate—the focus is on enhancing the GA’s convergence through two strategies: (1) a fuzzy-logic mechanism that chooses the mutation probability and (2) a regression-tree-based machine learning (AI) model trained on early generation data. Simulation results indicate improved convergence speed and better  $S_{11}$  performance for both approaches, with the AI-based mutation technique offering additional gains through real-time data-driven adaptation of the mutation probability.

## I. INTRODUCTION

Genetic algorithms (GAs) have shown significant promise in antenna optimization; however, premature convergence often hampers their effectiveness [1]. Researchers have thus proposed numerous adaptive methods to mitigate this limitation. One approach modifies the mutation probability based on population diversity metrics [2]. Still another study demonstrates the potential of GAs in microstrip patch antenna miniaturization by discretizing the radiating surface into small pixel elements [3]. Beyond mutation function applications, GA was also optimized by improving the selection of the first population using AI [4].

In parallel, fuzzy logic has been applied to adapt crossover and mutation probabilities, thereby balancing exploration and exploitation [5], [6]. A foundational overview of genetic algorithms—along with insights on such adaptive mechanisms—can be found in [7].

Building on these prior works, we address a microstrip patch antenna optimization problem that follows the pixel-based geometry approach [3], with a special emphasis on accelerating GA convergence. We introduce two adaptive mutation probability methods: a fuzzy-logic scheme and a machine learning approach that employs a regression tree trained on the first 20 generations of GA runs. As shown in later sections, both adaptive methods outperform baseline GAs (with fixed mutation rates) in terms of convergence speed and final  $S_{11}$  performance, with the machine learning approach offering additional benefits through data-driven real-time parameter tuning.

## II. ANTENNA GEOMETRY AND GA FRAMEWORK

### A. Antenna Geometry

We adopt the microstrip patch antenna design described in detail in [3], which discretizes a rectangular patch into a  $10 \times 10$

grid (“pixel” approach). The patch dimension is chosen so that the antenna resonates around 2.16GHz. An FR4 substrate of thickness 1.6mm underlies the patch.

### B. Overlap Handling

Adjacent pixels in diagonal contact [1 0; 0 1] or [0 1; 1 0] are made electrically continuous by overlapping them by 0.2mm. This ensures reliable conduction along the patch edges as shown in Fig. 1.

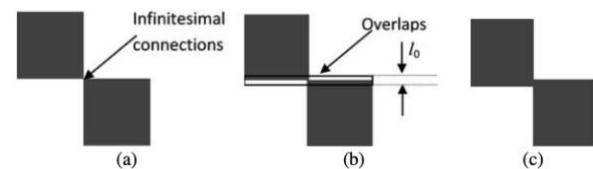


Figure 1. (a) Traditional on/off building blocks with infinitesimal connections. (b) Proposed overlapping scheme. (c) A possible structure with overlapping. [3]

### C. Genetic Algorithm Setup

The genetic algorithm optimizes a binary chromosome of length  $10 \times 10 = 100$ , indicating whether a cell is “on” (1) or “off” (0). The objective function (1) is as follows:

$$\text{cost} = \begin{cases} |S_{11}(f_i)| \cdot e^{(-20 \cdot \frac{|f_{\text{res}} - f_d|}{f_d})}, & f_d - \epsilon < f_i < f_d + \epsilon \\ \left| \frac{1}{N} \sum_{i=1}^N |S_{11}(i)| \right| & \text{otherwise} \end{cases} \quad (1)$$

where  $f_i$  is the Sampling frequency,  $N$  is the total number of sampling points,  $f_d$  is the desired frequency,  $f_{\text{res}}$  is the individual resonance frequency,  $S_{11}$  is the S-parameters of the antenna at resonance frequency, and  $\epsilon$  is 0.1

In this study, the target frequency  $f_d = 2.16$  GHz, is used. Lower cost corresponds to improved  $S_{11}$  performance near 2.16 GHz.

We use MATLAB’s Global Optimization Toolbox (specifically the ga function) to implement and run the genetic algorithm. The GA proceeds through the following stages:

- Initialization: A population of candidate solutions (i.e., binary chromosomes indicating which pixels are “on” or “off”) is randomly generated.
- Fitness Evaluation: Each individual’s cost is computed by constructing a `pcbStack` antenna (as described above) and then measuring the total penalty (1).

- Selection: The GA chooses individuals with higher fitness (lower cost) for reproduction. Common selection mechanisms include tournament or roulette-wheel selection.
- Crossover: Selected parents produce offspring.
- Mutation: This step introduces diversity by flipping bits in the chromosome with some probability.
  - In the GA, a fixed probability  $\alpha$  is used.
  - In the Fuzzy logic approach,  $\alpha$  is updated using fuzzy rules.
  - In the AI approach,  $\alpha$  is predicted by a regression tree.
- Termination: The GA iterates until it meets a stopping criterion, such as a set number of generations.

By adjusting the mutation probability adaptively (via fuzzy logic or AI), our method aims to accelerate convergence while avoiding premature stagnation in local optima.

### III. ADAPTIVE MUTATION STRATEGIES

#### A. Fuzzy Logic for Mutation Probability

The standard deviation  $\text{popStd}$  for each design variable within the population was calculated using:

$$\text{popStd} = \text{std}(\text{population}, 0, 1) \quad (2)$$

where  $\text{std}$  computes the standard deviation of each pixel. The diversity metric was then determined as the average of the standard deviations across all variables:

$$\text{diversity} = \text{mean}(\text{popStd}) \quad (3)$$

To enhance the optimization process, a fuzzy logic-based adaptive mutation strategy was implemented. When the diversity metric is low, or when the improvement in the solution stagnates, the mutation probability is increased to mitigate the risk of the algorithm getting trapped in a local optimum. Conversely, when the diversity metric is high, the mutation probability is reduced to enable finer refinement of the current solution. In this study, two mutation probability values were utilized: 5% for high diversity and 25% for low diversity.

#### B. Machine Learning (AI) for Mutation Probability

- For the initial 20 generations, choose a random mutation probability  $P(\text{mutation})$

$$P(\text{mutation}) = 0.01 + 0.3 \cdot \text{rand} \quad (4)$$

where  $P(\text{mutation})$  varies between 1% and 30%, and  $\text{rand}$  is a random function returning a real number between 0 and 1.

- Data collection: recording features:
  - Best score in the current population

- Mean score of the current population
- Diversity of the current population
- Improvement in score of the current population compared to the previous one.
- Chosen mutation probability  $P(\text{mutation})$ .

- Training phase:

Once the first 20 generations complete, a regression tree was fitted using the aforementioned data points to predict the best mutation probability.

- Later generations:

After the initial 20 generations, new features are computed at each iteration, and the trained regression tree predicts the optimal mutation probability. This probability is then applied to the GA, enabling dynamic adaptation.

## IV. RESULTS AND DISCUSSION

To evaluate our antenna designs, we compare four final configurations:

**GA-Optimized Antenna:** Evolved using a standard GA with a fixed mutation probability  $\alpha = 0.02$  (2%), shown in Fig. 2.

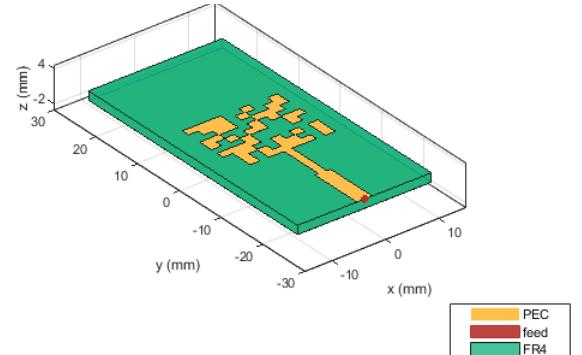


Figure 2. GA-optimized antenna (fixed mutation).

**Fuzzy-Optimized Antenna:** where the mutation probability is governed by fuzzy rules Fig. 3.

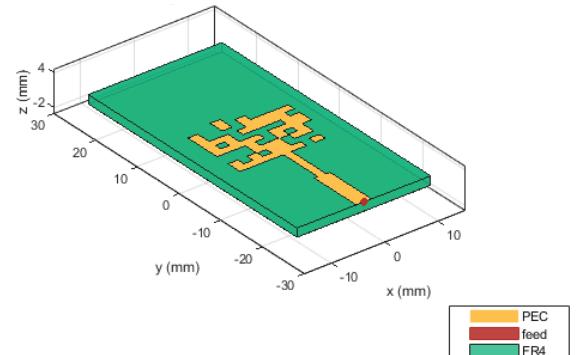


Figure 3. Fuzzy-optimized antenna.

**AI-Optimized Antenna:** where the GA learns a regression-tree model of mutation probability from the first 20 generations and applies it to subsequent generations Fig. 4.

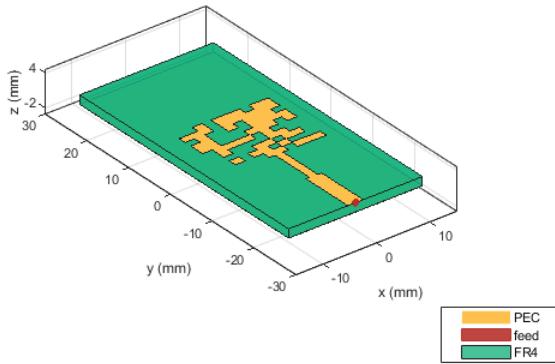


Figure 4. AI-optimized antenna (trained regression tree).

We focus on two key performance metrics, score vs. generations and return loss of the best design.

#### A. Fitness (score) Improvements

In our experiments, Fuzzy logic optimization yields approximately 5% improvement over the baseline, whereas AI yields around 7.5%. The regression tree's data-driven adaptation typically outperforms the fuzzy rule set, although both outperform the fixed-mutation strategy.

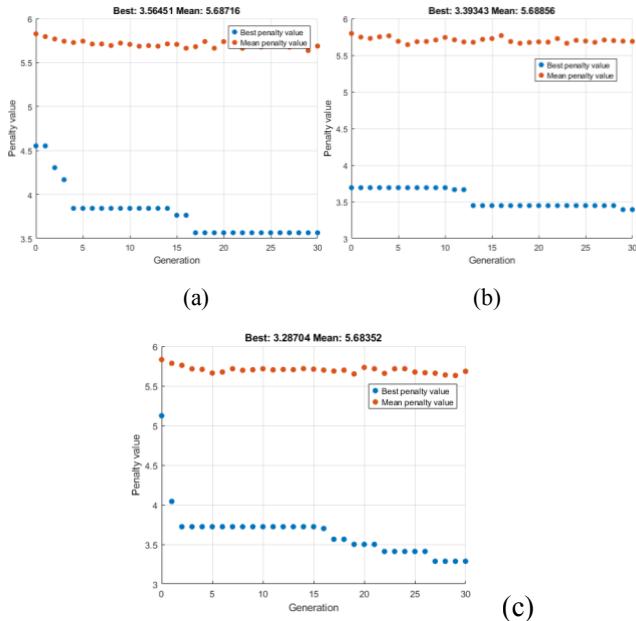


Figure 5. Comparison of convergence speed between (a) fixed probability GA, (b) Fuzzy logic, and (c) AI adaptive mutation probabilities.

#### B. Return loss Improvements

Simulations confirm that fuzzy logic optimization provides about 4 dB better matching in  $|S_{11}|$  than the baseline, while the AI approach further improves it by another 1 dB.

As shown in Fig. 6, the AI solution demonstrates the deepest  $|S_{11}|$  among the 3 methods.

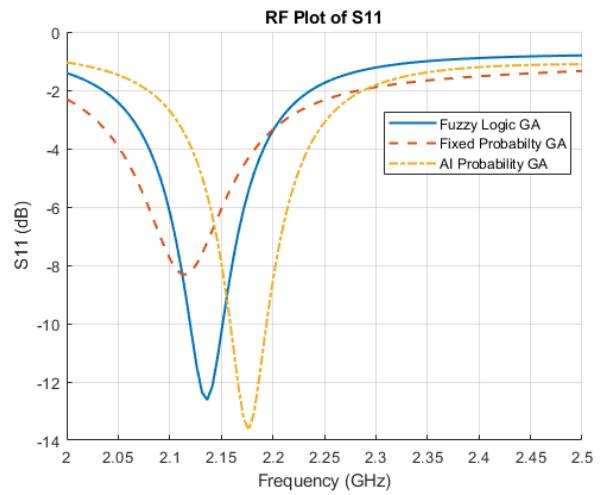


Figure 6. Comparison of return loss curves for fixed probability GA, Fuzzy logic, and AI adaptive mutation probabilities.

## V. CONCLUSION

We presented an adaptive mutation scheme for genetic algorithm-based microstrip patch antenna optimization, comparing a fuzzy logic strategy with a novel machine learning–driven regression tree approach. By accumulating training data in the early generations, the AI model learned to predict advantageous mutation probabilities, leading to faster and more robust convergence. Simulation results confirmed that both adaptive methods outperform fixed-probability GAs in terms of convergence speed and  $|S_{11}|$  performance, with the machine learning framework providing the highest gains.

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