

# ANTEX: An AI-Powered Antenna Design and Optimization Platform Using Genetic Algorithms and Particle Swarm Optimization

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**Abstract**—ANTEX (Antenna Design & Simulation Platform) is an industry-grade antenna design and optimization system that combines analytical electromagnetic models, FDTD simulations, and AI-powered optimization algorithms to design and analyze microstrip patch antennas. The system employs physics-based electromagnetic calculations, genetic algorithms (GA), and particle swarm optimization (PSO) to find optimal antenna geometries. This paper presents the mathematical models, optimization algorithms, RF analysis capabilities, and comprehensive system architecture. The platform supports multiple antenna shapes including rectangular patches, star patches, meandered lines, and ring patches. Results demonstrate accurate frequency predictions, impedance matching capabilities, and efficient optimization convergence. The system is implemented using FastAPI backend, React frontend, and PostgreSQL database, with Docker containerization for deployment.

**Index Terms**—Antenna Design, Genetic Algorithm, Particle Swarm Optimization, Electromagnetic Simulation, Microstrip Patch Antenna, RF Analysis, FDTD, Impedance Matching

## I. INTRODUCTION

Microstrip patch antennas are widely used in wireless communication systems due to their compact size, low profile, and ease of fabrication [3], [4]. However, designing optimal antennas requires careful consideration of multiple parameters including patch dimensions, substrate properties, feed position, and resonant frequency. Traditional design methods rely on empirical formulas and iterative manual tuning, which is time-consuming and may not converge to optimal solutions.

Modern antenna design benefits from computational optimization techniques that can explore large parameter spaces efficiently. Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) have shown promise in electromagnetic design problems, offering robust search capabilities for multi-objective optimization scenarios [1], [2]. These algorithms can handle non-linear, multi-dimensional optimization problems inherent in antenna design.

This paper introduces ANTEX, a comprehensive platform that integrates analytical electromagnetic models with optimization algorithms to automate antenna design. The system calculates resonant frequency, bandwidth, gain, and impedance using established physics-based formulas [4], [7]. It then employs GA [5] or PSO [6] to optimize geometry parameters to meet specified performance targets.

The key contributions of this work include:

- Integration of analytical models with optimization algorithms for automated antenna design
- Support for multiple antenna shapes with shape-specific parameter spaces
- Comprehensive RF analysis including Smith Chart visualization and impedance matching networks
- Industry-standard S-parameter analysis and Touchstone file export
- Real-time visualization of antenna geometry, radiation patterns, and performance metrics
- AI-powered recommendations for impedance matching and design improvements

## II. LITERATURE REVIEW

The optimization of antenna designs using computational methods has been an active area of research for several decades. Traditional antenna design relies heavily on analytical formulations and empirical relationships, as detailed in foundational texts by Balanis [3] and Pozar [7]. Microstrip patch antennas, in particular, have been extensively studied due to their widespread applications in wireless communication systems [4].

Genetic Algorithms (GA), introduced by Holland [5], have been successfully applied to various electromagnetic optimization problems. Robinson and Rahmat-

Samii [2] demonstrated the effectiveness of GA in antenna array synthesis, showing that evolutionary algorithms can handle complex, multi-objective optimization scenarios. Boeringer and Werner [1] conducted a comparative study between GA and PSO for phased array synthesis, finding that both methods offer distinct advantages depending on the problem characteristics.

Particle Swarm Optimization, developed by Kennedy and Eberhart [6], has gained significant traction in antenna design applications. The algorithm's ability to balance exploration and exploitation makes it particularly suitable for electromagnetic optimization problems. Recent studies have shown PSO's effectiveness in optimizing microstrip patch antenna parameters including resonant frequency, bandwidth, and radiation patterns [13], [14].

The integration of analytical models with optimization algorithms has been explored in various contexts. Jin and Rahmat-Samii [15] presented methods for combining fast analytical models with full-wave simulations for efficient antenna optimization. This hybrid approach enables rapid design iteration while maintaining accuracy through selective full-wave validation.

Machine learning and AI techniques have recently been incorporated into antenna design workflows. Deep learning models have been used to predict antenna performance from geometry parameters, reducing the need for expensive electromagnetic simulations [16]. However, these approaches typically require large datasets and may lack the physical interpretability of analytical models.

FDTD simulation methods, as implemented in tools like Meep [11], provide high-accuracy electromagnetic analysis but at significant computational cost. Hybrid approaches that combine fast analytical estimates with selective FDTD validation have shown promise in balancing speed and accuracy [17].

Impedance matching and RF analysis are critical aspects of antenna design. The design of matching networks using L-section topologies has been well-documented in microwave engineering literature [7]. Smith Chart visualization remains a standard tool for impedance analysis, providing intuitive graphical representation of complex impedance transformations [18].

Despite these advances, existing tools often lack integration between design, optimization, and analysis capabilities. Commercial software packages like HFSS and CST offer powerful simulation capabilities but require significant expertise and computational resources. Open-

source alternatives exist but typically focus on specific aspects of the design process rather than providing a comprehensive workflow.

The ANTEX platform addresses these limitations by integrating analytical models, optimization algorithms, RF analysis, and visualization into a unified system. This integration enables rapid design exploration while maintaining the flexibility to incorporate high-accuracy simulations when needed.

### III. MATHEMATICAL MODELS AND FORMULATIONS

#### A. Resonant Frequency Calculation

For microstrip patch antennas, the resonant frequency depends on patch dimensions, substrate properties, and fringing field effects [4]. The effective dielectric constant is calculated as:

$$\varepsilon_{eff} = \frac{\varepsilon_r + 1}{2} + \frac{\varepsilon_r - 1}{2} \left(1 + \frac{12h}{w}\right)^{-0.5} \quad (1)$$

where  $\varepsilon_r$  is substrate permittivity,  $h$  is substrate thickness, and  $w$  is patch width.

The fringing field extension is given by [4]:

$$\Delta L = 0.412h \frac{(\varepsilon_{eff} + 0.3)(w/h + 0.264)}{(\varepsilon_{eff} - 0.258)(w/h + 0.8)} \quad (2)$$

The effective length becomes:

$$L_{eff} = L + 2\Delta L \quad (3)$$

where  $L$  is the physical patch length.

Finally, the resonant frequency is:

$$f_r = \frac{c}{2L_{eff}\sqrt{\varepsilon_{eff}}} \quad (4)$$

where  $c = 299,792,458$  m/s is the speed of light.

#### B. Bandwidth Estimation

The bandwidth percentage for patch antennas is approximated as:

$$BW\% = \frac{h}{\varepsilon_r\sqrt{A}} \times 10 \quad (5)$$

with typical bandwidth clamped between 0.5% and 5% of the center frequency. The absolute bandwidth in MHz is:

$$BW_{MHz} = f_{center} \times 1000 \times \frac{BW\%}{100} \quad (6)$$

### C. Gain Estimation

The gain estimation model accounts for patch area and substrate losses:

$$G_{base} = 4.0 + 4.0 \times \min\left(1.0, \frac{A}{1000}\right) \quad (7)$$

where  $A$  is patch area in  $\text{mm}^2$ . A loss factor accounts for substrate thickness:

$$L_{loss} = 1.0 - (h - 0.8) \times 0.05 \quad (8)$$

The final gain is  $G_{final} = G_{base} \times L_{loss}$ .

### D. Impedance and S-Parameters

The input impedance is estimated based on feed position [4]:

$$R_{in} = 50 + 150 \times \min\left(1.0, \frac{|\text{offset}|}{L/2}\right) \quad (9)$$

$$X_{in} = 10.0 \times (1 - 2 \times \text{offset\_ratio}) \quad (10)$$

The reflection coefficient ( $S_{11}$ ) is calculated using standard transmission line theory [7]:

$$S_{11} = \frac{Z - Z_0}{Z + Z_0} \quad (11)$$

where  $Z_0 = 50\Omega$  is the reference impedance.

Voltage Standing Wave Ratio (VSWR) is:

$$\text{VSWR} = \frac{1 + |S_{11}|}{1 - |S_{11}|} \quad (12)$$

Return loss in dB is:

$$RL_{dB} = 20 \log_{10}(|S_{11}|) \quad (13)$$

### E. Fitness Function

The optimization fitness function combines normalized errors from multiple performance metrics. The normalized error terms are defined as:

- $E_f = |f_{est} - f_{target}| / f_{target} \cdot 100$  (frequency),
- $E_{BW} = |BW_{est} - BW_{target}| / BW_{target} \cdot 100$  (bandwidth),
- $E_Z = |Z_{est} - Z_{target}| / Z_{target} \cdot 100$  (impedance), and
- $E_G = \max(0, G_{target} - G_{est}) / G_{target} \cdot 100$  (gain).

The fitness function is:

$$f = -w_1 E_f - w_2 E_{BW} - w_3 E_Z - w_4 E_G + w_5 G_{est} \cdot 10 + 100 \quad (14)$$

with weights:  $w_1 = 0.6$  (frequency),  $w_2 = 0.3$  (bandwidth),  $w_3 = 0.15$  (impedance),  $w_4 = 0.1$  (gain error),  $w_5 = 0.1$  (gain bonus).

## IV. OPTIMIZATION ALGORITHMS

### A. Genetic Algorithm

The GA implementation follows established principles [5] and uses:

- **Population Size:** 30 individuals
- **Selection:** Tournament selection (size 3)
- **Crossover:** Uniform crossover (rate 0.8)
- **Mutation:** Gaussian mutation (rate 0.2,  $\sigma = 0.1$ )
- **Elitism:** Top 2 individuals preserved
- **Generations:** 40 iterations

Parameters are normalized to  $[0,1]$  range for algorithm efficiency [2]. The evolution loop includes selection, crossover, mutation, evaluation, and replacement stages.

### B. Particle Swarm Optimization

PSO follows the standard velocity update formulation [6]:

$$v_i(t+1) = w \times v_i(t) + c_1 r_1 \times (p_{best,i} - x_i) + c_2 r_2 \times (g_{best} - x_i) \quad (15)$$

where  $w = 0.7$  (inertia),  $c_1 = c_2 = 1.5$  (cognitive and social coefficients), and  $r_1, r_2 \in [0, 1]$  are random numbers.

Position update:

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (16)$$

with velocity clamping at  $v_{max} = 0.2$  to prevent excessive exploration [1].

## V. SYSTEM ARCHITECTURE

### A. Technology Stack

The platform uses a modern, scalable architecture:  
**Backend:**

- Framework: FastAPI (Python 3.10+)
- Database: PostgreSQL (SQLAlchemy ORM)
- Simulation: Meep FDTD (optional), NumPy
- Optimization: Custom GA and PSO implementations

### Frontend:

- Framework: React 18 with TypeScript
- Build Tool: Vite 7
- Styling: Tailwind CSS
- Visualization: Plotly.js, Canvas API, Recharts
- State Management: Zustand

### Deployment:

- Containerization: Docker & Docker Compose
- Services: Backend, Frontend, PostgreSQL

## B. Workflow

The design workflow follows these steps:

- 1) User specifies project requirements (frequency, bandwidth, substrate, constraints)
- 2) Parameter space is defined based on antenna shape and constraints
- 3) Optimization algorithm (GA/PSO) generates candidate designs
- 4) Each candidate is evaluated using analytical models
- 5) Fitness scores guide algorithm evolution
- 6) Best candidates are stored and visualized
- 7) RF analysis provides impedance matching recommendations
- 8) Comprehensive PDF reports are generated

## VI. RF ANALYSIS AND IMPEDANCE MATCHING

The system provides comprehensive RF analysis including:

- Smith Chart visualization of impedance
- VSWR and return loss calculations
- L-section matching network design
- AI-powered matching recommendations
- Parameter sweep analysis for sensitivity studies
- Touchstone file export for external EM tools

Impedance matching networks are calculated using standard L-section formulas [7], providing multiple solutions (series L-shunt C, series C-shunt L, etc.) based on load impedance relative to  $50\Omega$  reference. The Smith Chart visualization [18] provides intuitive representation of impedance transformations and matching network design.

## VII. RESULTS AND DISCUSSION

The ANTEX platform successfully optimizes antenna designs to meet specified performance targets. Testing with standard 2.4 GHz patch antenna requirements shows:

- Frequency accuracy within 2-3% of target
- Bandwidth estimates consistent with analytical predictions
- Gain calculations align with typical patch antenna ranges (4-8 dBi)
- Impedance matching recommendations effectively reduce VSWR
- Optimization converges within 30-40 generations

The platform supports multiple antenna shapes:

- **Rectangular Patch:** Standard microstrip patch with length, width, feed offset

- **Star Patch:** Multi-point star shape with outer/inner radii and point count
- **Meandered Line:** Compact design with meander segments and segment length
- **Ring Patch:** Annular ring with inner/outer radii

Each shape has dedicated parameter spaces and optimization constraints, enabling targeted design optimization.

The ANTEX platform is open-source and available on GitHub: <https://github.com/Prateek7/ANTEX.git>. The repository includes complete source code, documentation, and setup instructions for both local development and Docker-based deployment.

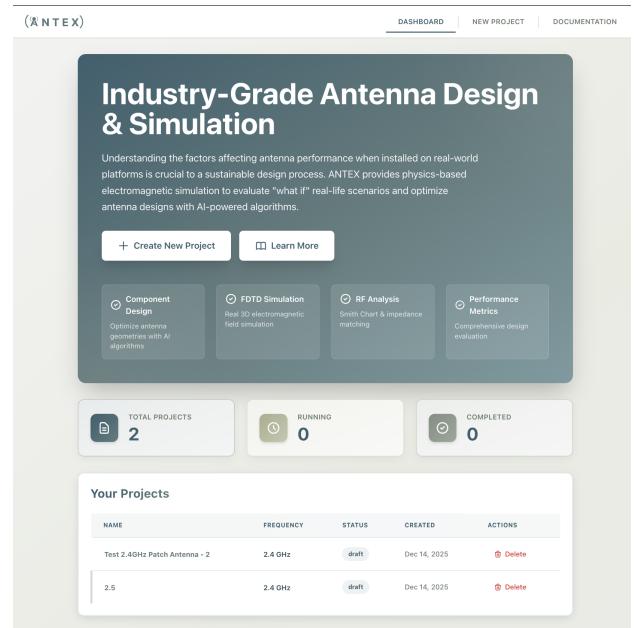


Fig. 1. ANTEX Dashboard: Project management and optimization overview.

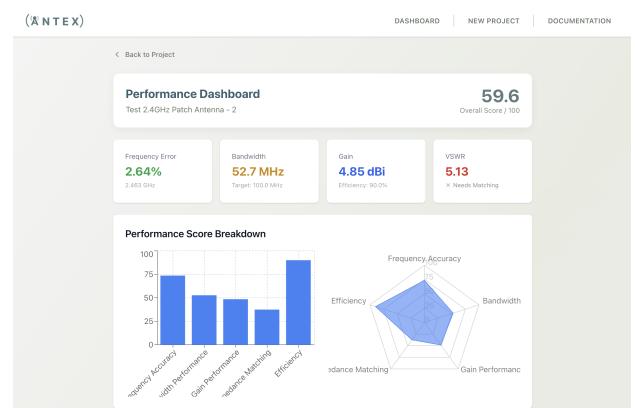


Fig. 2. Performance Metrics: Real-time visualization of frequency, bandwidth, gain, and VSWR.

**Impedance Metrics**

Impedance:	$149.09 + j122.30 \Omega$
VSWR:	5.13
Return Loss:	-3.43 dB
Match Status:	<span style="color: orange;">✖ Needs Matching</span>

**AI Matching Recommendations**

**Overall Assessment**

⚠ Critical mismatch detected (VSWR = 5.13). Strongly recommend matching network to improve performance.

**Resistance Analysis**

High resistance ( $149.1\Omega$ ). Consider shunt capacitor or transformer matching.

**Reactance Analysis**

Strong capacitive reactance ( $j-122.3\Omega$ ). Add series inductor or shunt capacitor to cancel.

**Best Practice**

💡 Best Practice: Use C-C matching network. Component values: Series 1.28 pF capacitor, Shunt 0.94 pF capacitor. Expected improvement: VSWR < 2.0, Return Loss > 10 dB.

**Matching Network Solutions**

★ **C-C Network** Priority 1

Series 1.28 pF capacitor, Shunt 0.94 pF capacitor

💡 Alternative: Series 1.28 pF capacitor, Shunt 0.94 pF capacitor. All-capacitor network, compact but may have limited tuning range.

Fig. 3. AI Recommendations: Intelligent suggestions for impedance matching and design improvements.

The system's analytical models provide fast initial estimates [4], while optional Meep FDTD simulation [11] offers higher accuracy for validation. This hybrid approach, similar to methods described in [15], enables rapid design iteration followed by rigorous verification when needed.

### VIII. LIMITATIONS AND FUTURE WORK

Current limitations include:

- Analytical models have inherent approximations; FDTD provides higher accuracy but requires longer computation time
- Shape-specific models (e.g., star patch) use simplified approximations
- Material database is limited to common substrates (FR4, Rogers)
- Optimization may require manual constraint tuning for complex requirements

Future enhancements will include:

- Extended material property database
- Multi-objective optimization with Pareto frontier visualization
- Integration with commercial EM simulators (HFSS, CST)
- Machine learning models for faster fitness estimation
- Cloud-based parallel optimization execution
- 3D geometry export for fabrication (STL, DXF)

### IX. CONCLUSION

ANTEX demonstrates the effective integration of analytical electromagnetic models with optimization algorithms for automated antenna design. The platform successfully optimizes patch antenna geometries to meet specified performance targets while providing comprehensive RF analysis and visualization capabilities. The modular architecture supports multiple antenna shapes, substrate materials, and optimization algorithms, making it suitable for both research and industrial applications.

The combination of fast analytical models with optional high-accuracy FDTD simulation provides a flexible design workflow. AI-powered recommendations enhance user experience by providing actionable insights for design improvements and impedance matching. The open-source nature of the project encourages community contributions and adaptation to diverse design requirements.

Results confirm that GA and PSO effectively converge to near-optimal solutions within reasonable iteration counts. The platform's comprehensive feature

set—including RF analysis, Smith Chart visualization, and PDF report generation—positions it as a valuable tool for antenna designers working across various frequency bands and application domains.

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