Report on Dielectric Lens Optimization Using Neural Networks and Genetic Algorithms

Summary:

This report investigates the optimization of dielectric lens (DLen) designs for a pulsed high-powered Microwave (HPM) biconical antenna (Bicone) operating at 500 MHz using an integrated approach of neural networks and genetic algorithms. Neural networks were trained to serve as surrogate models, predicting antenna performance metrics from lens geometries without relying on computationally intensive full-wave electromagnetic simulations. These surrogate models were incorporated into a genetic algorithm framework, which iteratively evolved lens designs through selection, crossover, and mutation. This integrated methodology aimed to enhance the electric field intensity at 500 MHz, thereby improving the Bicone HPM effector's power spectral density.

Traditional optimization methods rely on human-designed geometries and exhaustive full-wave electromagnetic simulations (EM). These methods are limited by human intuition and are computationally intensive in terms of time, processing power, and energy consumption. To overcome these limitations, the research integrated neural networks and genetic algorithms (GAs) to efficiently explore the vast design space and discover novel DLen geometries that could potentially outperform designs optimized by other sophisticated ways like the full-wave EM, which are heavy on the computational resources in terms of time, processing power, and ultimately energy.

A MATLAB script was developed to automate the generation of random lens geometries within specified boundaries, resulting in a dataset of over 10,000 samples. These lens geometries were simulated using CST Studio Suite to obtain the electric field in the frequency and time domain. This dataset was used to train neural networks to predict antenna performance metrics from DLen geometries created by the GA.

While the primary objectives faced significant challenges, the project yielded several minor accomplishments. Notably, the extensive dataset of over 10,000 lens geometries and their corresponding performance metrics represents a valuable resource for future research in electromagnetic design optimization. Additionally, the integration of CST Studio Suite with MATLAB for automated model generation and simulation established a workflow that can be refined in future studies. The exploration of various neural network architectures and regularization techniques provided insights into their applicability for surrogate modeling in complex electromagnetic systems.

Despite extensive efforts, the neural networks did not achieve the desired predictive accuracy due to high degrees of freedom (DOF), insufficient data representation, and computational constraints. Consequently, the genetic algorithm, relying on these neural networks for fitness evaluation, was unable to identify lens designs that outperformed the best randomly generated designs. The research identified several challenges, including the complexity of the design space, limitations in data collection processes, neural network performance issues, and software constraints.

Recommendations for future work include enhancing data collection methods (such as accelerating model generation and leveraging data augmentation), reducing problem complexity through simplification and feature engineering, improving neural network architectures with advanced modeling techniques, exploring alternative optimization strategies, addressing computational and software constraints, and fostering interdisciplinary collaboration.

By implementing these strategies, there is potential to overcome current limitations and achieve significant advancements in dielectric lens optimization for the 500 MHz biconical antenna. Such progress would contribute to the broader field of electromagnetic design optimization, demonstrating the viability of combining machine learning with evolutionary strategies in engineering applications.

1. Introduction

Dielectric lenses (DLes) are crucial components in enhancing the performance of antennas by focusing electromagnetic waves and improving parameters such as power density, bandwidth, and impedance matching. Optimizing the geometry and material properties of these lenses is critical, especially when dealing with high-power pulse applications.

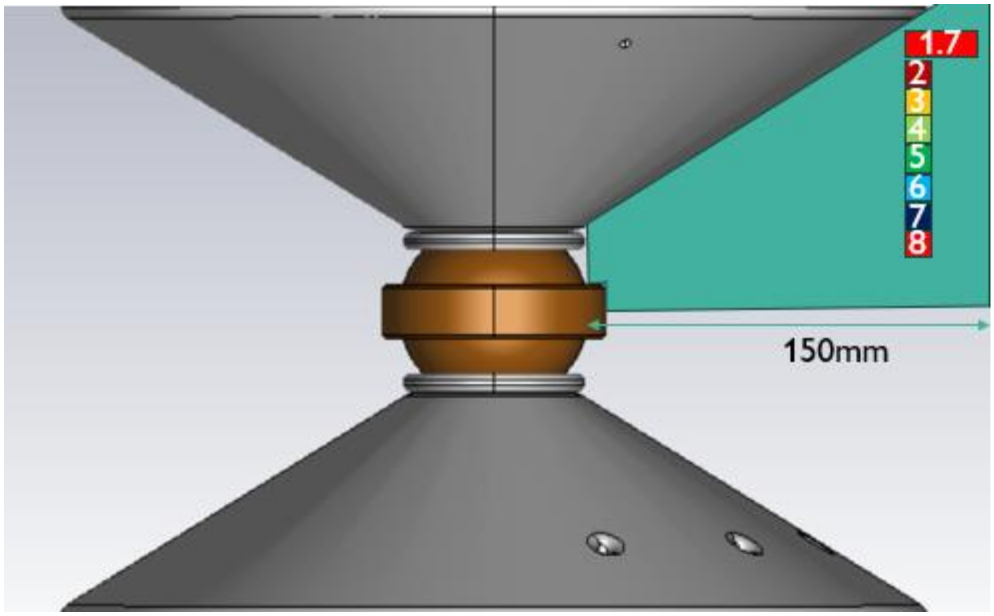
One such application involves a high pulse-powered biconical antenna with an omnidirectional radiation profile, designed to operate at 500 MHz. This antenna is driven by a pulse that is approximately a few nanoseconds wide. In the base case without a dielectric lens (DLen), the Fast Fourier Transform (FFT) of the antenna's output displays the electric field intensity (in V/MHz × 10^4) along the y-axis, with frequency (in GHz) on the x-axis. The peak electric field intensity occurs slightly above 500 MHz, reaching approximately 2.0 V/MHz × 10^4.

The goal is to use a dielectric lens to increase the electric field intensity at exactly 500 MHz or shift the peak closer to this frequency, thereby enhancing the antenna's performance at the desired operational frequency.

Traditional optimization methods rely heavily on human-designed geometries and exhaustive full-wave electromagnetic simulations to explore the design space. However, human-made geometries may not fully capture the optimal configurations due to limitations in creativity and the inability to consider the vast number of possible designs. Moreover, exhaustive simulations are computationally intensive and time-consuming, making it impractical to thoroughly explore large and complex design spaces.

To overcome these challenges, this research explores the integration of neural networks and genetic algorithms (GAs) to efficiently optimize dielectric lens designs. By leveraging machine learning and evolutionary strategies, we aim to discover novel lens geometries that can enhance the antenna's performance at 500 MHz while reducing computational costs.

Figure 1: Original Available Search Space and Dielectric Constant Variations



Description: This figure shows the base case highlighting a quadrant of the available search space, with the dielectric constant varying from 1.7 to 8. The geometry of the lens and the varying dielectric constants are visually mapped, indicating the range of materials explored during optimization.

2. Purpose of the Research

The primary goal of this research was to develop a more efficient method for optimizing dielectric lenses by integrating neural networks and genetic algorithms (GAs). The objectives were:

- **To enhance the electric field intensity at exactly 500 MHz** for a high pulse-powered biconical antenna by optimizing the dielectric lens geometry, aiming to shift the peak electric field closer to the desired frequency.
- **To reduce computational time and resources** by employing neural networks as surrogate models to predict antenna performance metrics from lens geometries, minimizing reliance on computationally expensive simulations during the optimization process.
- **To leverage genetic algorithms** for effectively exploring the design space and evolving lens geometries toward optimal performance metrics, potentially discovering designs beyond human intuition.
- **To address limitations of human-made geometries** by utilizing algorithmic generation of lens designs, thereby considering a vast number of possible configurations that may yield superior performance.

3. Methodology

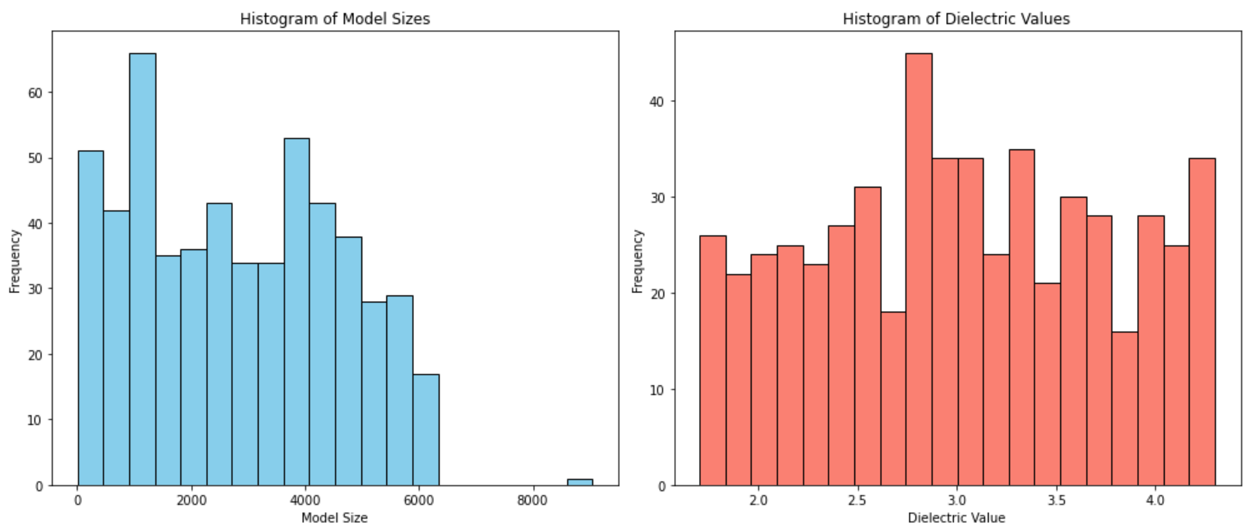
The research methodology comprised three main components: data collection, neural network development, and genetic algorithm optimization.

3.1 Data Collection

A MATLAB script (random_lens_data_creatorV3.mat) was developed to automate the generation of random lens geometries and simulate their performance using CST Studio Suite, a full-wave electromagnetic simulation software. The key features of the data collection process are:

- Algorithmic Lens Generation:
  - The algorithm can generate lens models with up to **100 origins**, where the lens "grows" randomly from these origins within specified boundaries.
  - The lens design boundaries are defined as **15 mm (y-axis inside height) × 135 mm (z-axis outside boundary)**, with a resolution of **1 mm × 1 mm**. This allows for fine-grained control over the lens geometry.
  - The original search space was a quadrilateral defined by a **15 mm (y-axis) inside height at the switch's 135 mm (z-axis) bottom edge** and a **135 mm (y-axis) outside height**, providing a large area for potential lens designs.
- Dataset Generation:
  - **6,894 samples** were collected for the original dataset, each representing a unique lens geometry and its corresponding performance metrics.
  - The large dataset was intended to provide sufficient coverage of the design space for training the neural networks.

Figure 2: Histograms of Model Sizes and Dielectric Values



Description: Two histograms are displayed—one showing the distribution of model sizes in the original search space, and another showing the distribution of dielectric constant values used in the early stages of design exploration.

- Challenges and Adjustments:

- The high complexity of the generated lens geometries posed computational challenges. CST Studio Suite struggled to handle these complex models, leading to failures in simulations.
    - To address this, the search space was reduced, effectively simplifying the lens geometries. This reduction was necessary to ensure that simulations could be completed successfully and that the neural networks could be trained effectively.
    - Validation of the models is critical and reducing the search space helped in managing model complexity while still exploring a meaningful range of designs.
- Simulation and Data Extraction:
    - The script interfaces with CST Studio Suite to run simulations for each generated lens design.
    - Relevant data, including **E-field versus frequency**, **E-field versus time**, and **impedance versus frequency**, are extracted and exported into text files for further analysis.
    - The lens geometries are mapped into a nodal format suitable for input into neural networks, effectively converting complex geometric data into structured numerical arrays.

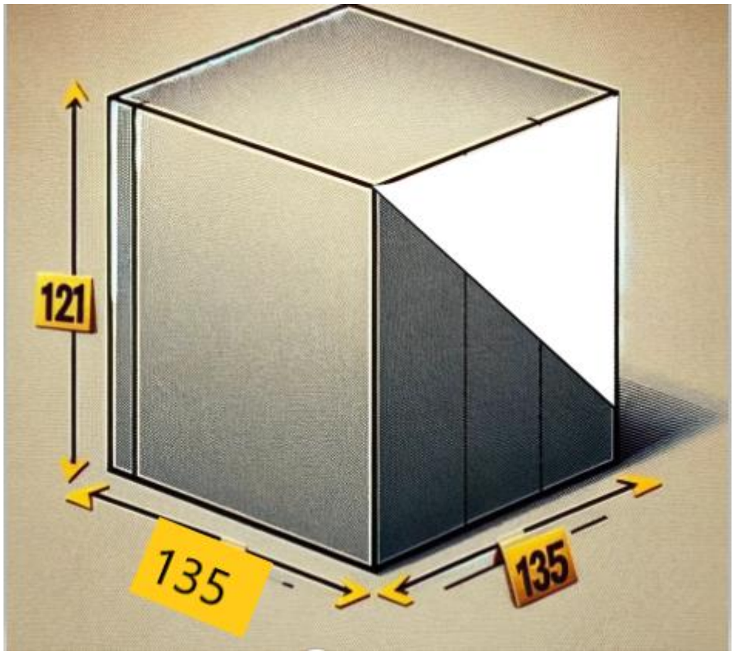
Over approximately two months, the data collection tool generated and simulated a total of **10,144 lens designs**. Despite the lengthy process, this dataset was intended to provide sufficient coverage of the design space for training the neural networks.

3.2 Neural Network Development

Neural networks of varying types were developed to predict antenna performance metrics based on the lens geometries. Several architectures and techniques were explored, including:

- **Deep neural networks** with varying numbers of layers and neurons to capture complex nonlinear relationships.
- **Activation functions** such as ReLU and ELU to introduce nonlinearity into the models.
- **Regularization techniques** like L1 regularization to prevent overfitting and improve generalization.
- **Batch normalization and dropout layers** to stabilize learning and further mitigate overfitting.
- **Data Preprocessing for CNN Input** was needed for the original dataset to ensure the data was suitable for CNN architectures, the non-square geometric data format (121 high on left, 135 wide at bottom, 14 high on right, slanted top boundary) needed to be modified to a square 135x135 format. This was achieved by adding a zero-padding region to the input data, effectively creating a consistent input shape required by CNNs.

Figure 3: Data Modification for CNN Input



Description: This figure explains the modification process applied to the geometric data to convert a non-square 121x135 grid to a square 135x135 grid, necessary for consistent input into CNNs. The visual representation of the modification clarifies the process of adding zero-padding.

The neural networks were trained using the collected dataset, aiming to accurately predict:

- **Spectral content at 500 MHz** from E-field versus frequency data.
- **Peak-to-peak E-field** from E-field versus time data.
- **Impedance characteristics**, providing a comprehensive understanding of lens performance.

3.3 Genetic Algorithm Optimization

A genetic algorithm was implemented to optimize the lens geometries using the neural networks as surrogate models for fitness evaluation. The process involved:

- **Initializing a population** of lens designs (individuals) with potential solutions.
- **Predicting performance** of each design using the trained neural networks, thus avoiding costly simulations.
- **Selecting, mating, and mutating individuals** based on their predicted fitness to evolve the population towards better designs over successive generations.

The optimization focused on maximizing metrics such as spectral content at 500 MHz and peak-to-peak E-field, with the ultimate goal of outperforming the best designs in the dataset.

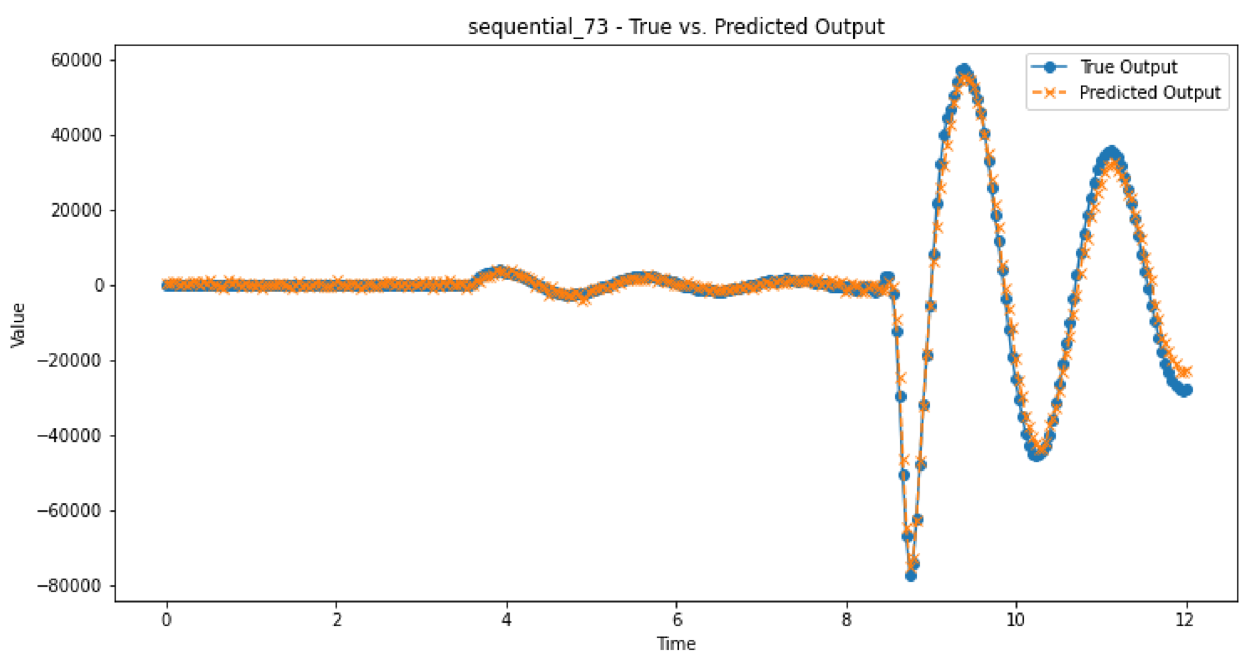
4. Results and Analysis

4.1 Neural Network Performance

Despite extensive training and experimentation with different architectures, the neural networks did not achieve the desired level of accuracy in predicting antenna performance metrics:

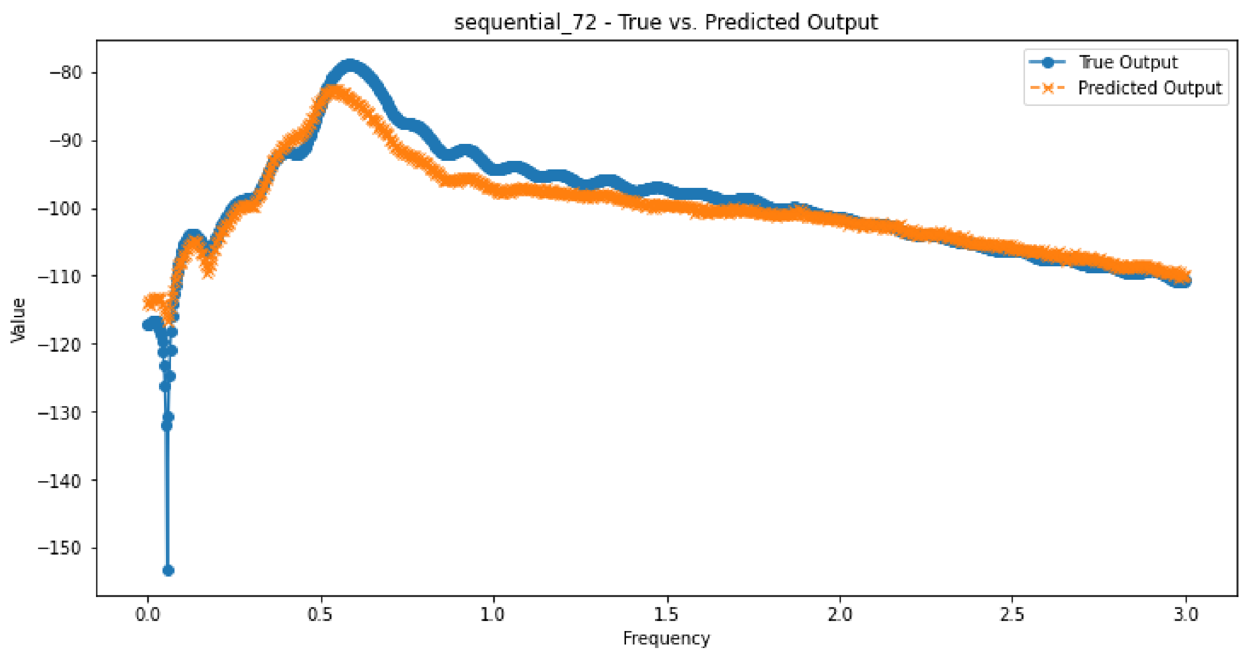
- **Predictive Accuracy:** The neural networks' mean squared error (MSE) at 500 MHz remained higher than acceptable thresholds. The initial models showed an MSE of 3.7370%, which only improved to 0.9555% after increasing the dataset size to 7,000 samples. The predictive accuracy of the neural networks significatly improved with the increased dataset size and reduced search space. The latest dataset of over 10,000 samples allowed for more accurate predictions of performance metrics at 500 MHz. A comparison of different neural network architecture performances, trained with this dataset, is provided in **Table 2** below. The models' mean squared error (MSE) at 500 MHz shows notable improvements compared to the initial dataset, with the **model_batchnorm** achieving the lowest MSE of 0.004635 V/mHz × 10^4 and a percentage MSE at 500 MHz of 0.299679%

Figure 4: True vs. Predicted Output (model trained on the original dataset)



Description: A plot comparing true and predicted output values over time for a sequential neural network model trained on the original dataset. The close alignment between the predicted and true outputs indicates the model's performance in the time domain.

Figure 5: True vs. Predicted Output (model trained on the original dataset)



Description: A plot comparing the true and predicted outputs over frequency for a sequential model. While the predictions closely match the true outputs across most frequencies, deviations are observed from 500 MHz to 1.5 GHz.

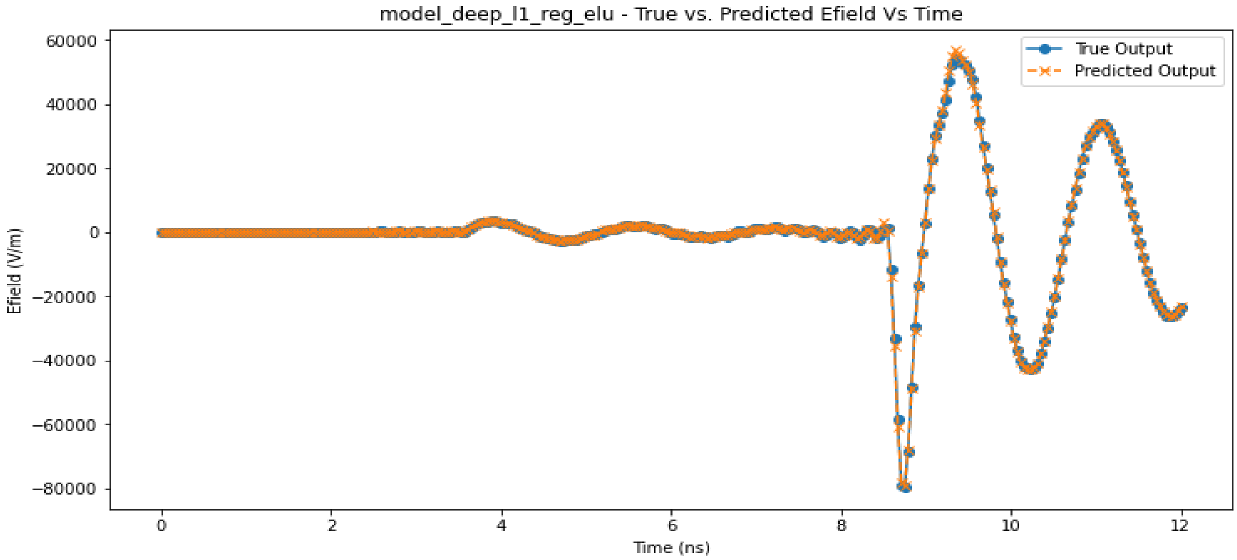
Table 1: Frequency Metrics Table (V/mHz × 10^4) (models trained on the original dataset)

Frequency Metrics Table (V/mHz * 10^4):

	Model Name	Val MAE Last Epoch	MSE @ 500 MHz	% MSE @ 500 MHz
0	model_basic	0.029920	0.046210	2.992140
1	model_deep_l1_reg_elu	0.007557	0.015918	1.030720
2	model_wide	0.026767	0.040194	2.602559
3	model_elu_activation	0.017920	0.038006	2.460935
4	model_sgd_optimizer	0.207776	0.204924	13.268966
5	model_batchnorm	0.092289	0.014805	0.958617
6	model_l1_regularization	0.007801	0.016229	1.050828

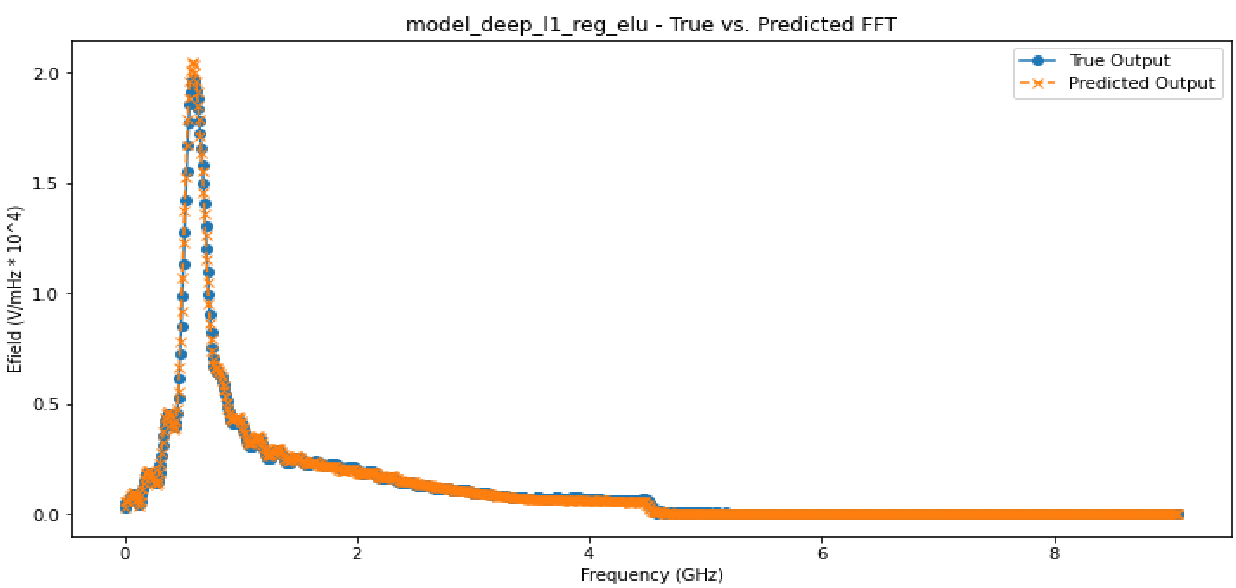
Description: This table compares the performance of various neural network models trained on the original dataset. Metrics include the validation mean absolute error (Val MAE) from the last epoch, mean squared error (MSE) at 500 MHz, and the percentage of MSE at 500 MHz. The **model_batchnorm** and **model_deep_L1_reg_elu** achieved the best performance, demonstrating the lowest MSE and percentage MSE at 500 MHz, making them the most accurate models in predicting the spectral content at the target frequency of 500 MHz.

Figure 6: Model Deep L1 Reg ELU - True vs. Predicted E-Field vs Time



Description: This plot illustrates the time-domain prediction of the electric field (V/m) for the deep L1 regularized ELU model. True vs. predicted values align closely over time, demonstrating the model's capacity to accurately predict peak-to-peak E-field values from time-domain data using the 10,000-sample dataset.

Figure 7: Model Deep L1 Reg ELU - True vs. Predicted FFT



Description: This plot compares the true output and predicted output of the electric field (E-field) in V/mHz × 10^4 as a function of frequency (GHz) for the deep L1 regularized ELU model. The close alignment between the true and predicted values, especially around the peak at 500 MHz, indicates the model's improved performance in predicting spectral content from the larger dataset.

Table 2: Frequency Metrics Table (V/mHz × 10^4) (models trained on the 10,000 sample dataset)

Frequency Metrics Table (V/mHz * 10^4):

	Model Name	Val MSE Last Epoch	MSE @ 500 MHz	% MSE @ 500 MHz
0	model_basic	0.001823	0.022235	1.437755
1	model_deep_l1_reg_elu	0.000425	0.018012	1.164704
2	model_wide	0.001761	0.021277	1.375825
3	model_elu_activation	0.000608	0.023249	1.503312
4	model_sgd_optimizer	0.045655	0.136587	8.832039
5	model_batchnorm	0.003015	0.004635	0.299679
6	model_l1_regularization	0.000423	0.017882	1.156285

Description: This table presents the performance of various neural network models in terms of validation mean squared error (MSE), MSE at 500 MHz, and percentage MSE at 500 MHz. The **model_batchnorm** and **model_L1_regularization** architectures achieve the lowest errors, indicating improved predictive accuracy for spectral content at 500 MHz in the reduced search space.

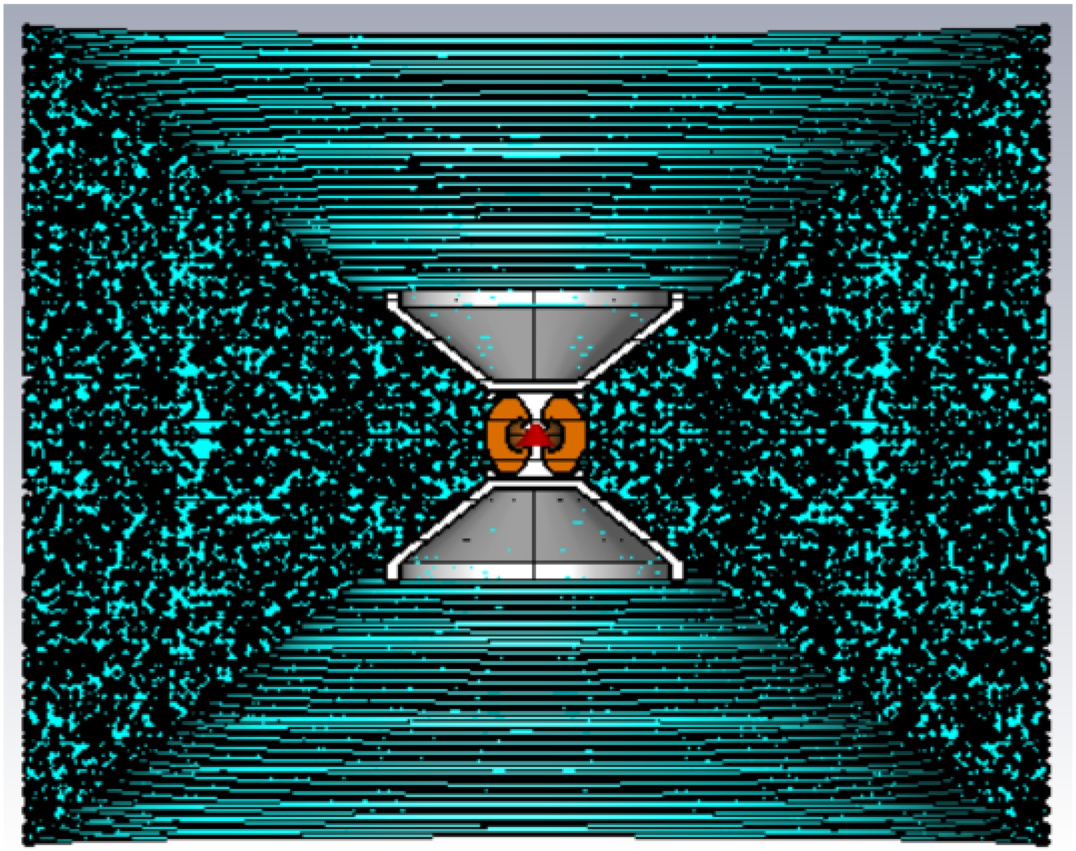
- **Generalization Issues:** The models struggled to generalize from the training data to unseen data, indicating overfitting or insufficient learning capacity.
- **Complex Relationships:** The high degrees of freedom (DOF) in lens geometries made it challenging for the neural networks to capture the intricate relationships between geometry and performance metrics.

4.2 Genetic Algorithm Performance

The genetic algorithm, relying on the neural networks for fitness evaluation, did not produce lens designs that outperformed the best random designs in the dataset:

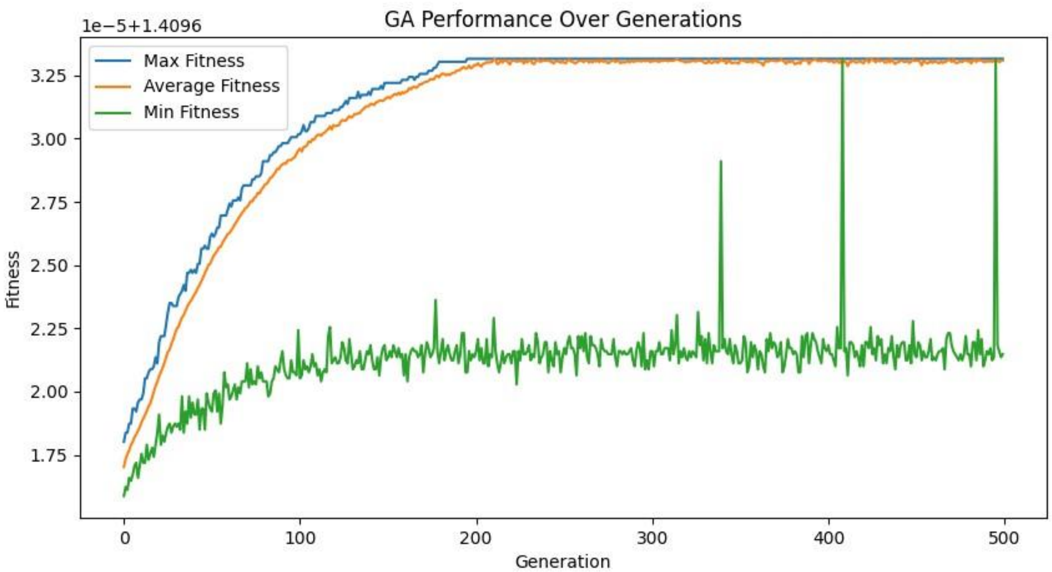
- **Suboptimal Designs:** The GA converged to designs with spectral content at 500 MHz lower than or equal to the best randomly generated designs. For example, it achieved a spectral content of 1.4096 (V/(m·Hz))·10^-5, whereas the best random design had 1.416 (V/(m·Hz))·10^-4.

Figure 8: GA-Optimized Lens Design Using NN Fitness Function Trained on Original Dataset (cross section view)



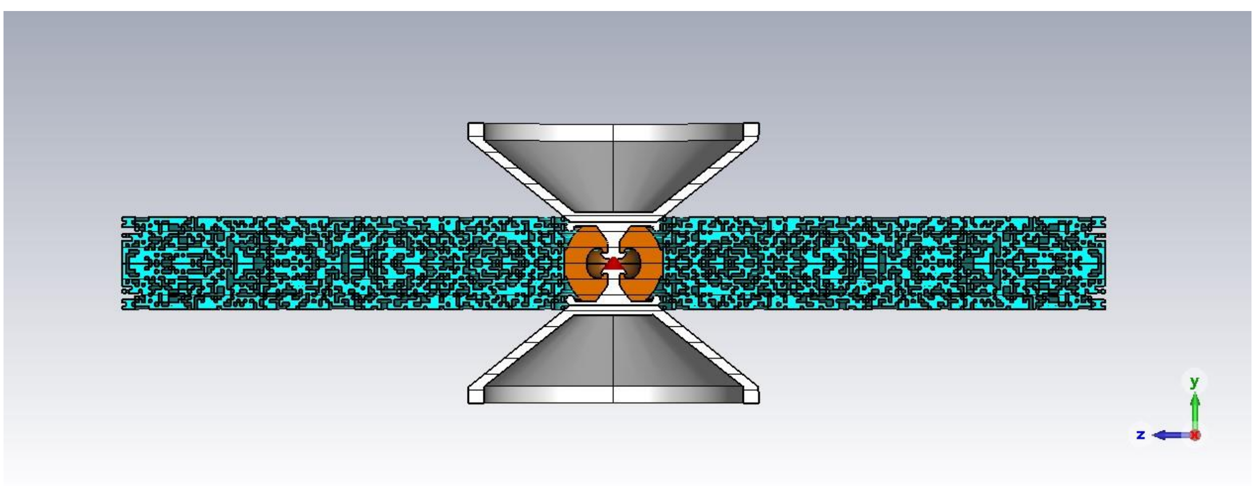
Description: This image illustrates the first dielectric lens design generated by a Genetic Algorithm (GA) using a neural network (NN) fitness function trained on the original dataset. The lens was built within the initial large search space and exhibits significant geometric complexity. However, this design did not significantly outperform random designs in terms of spectral content at 500 MHz due to inaccuracies in the neural network's fitness predictions.

Figure 9: GA Fitness Convergence Over Generations (NN Trained on 10,000 Sample Dataset)



Description: The plot depicts the Genetic Algorithm's fitness progression over 500 generations, using a neural network fitness function trained on the 10,000 sample dataset with a reduced search space. The maximum, average, and minimum fitness scores are shown. The GA demonstrates early improvement, but there is limited further convergence, indicating possible stagnation. The target frequency for optimization was 500 MHz, and the fitness metric focuses on spectral content.

Figure 3: GA-Optimized Lens Design Using NN Fitness Function Trained on 10,000 Sample Dataset (cross section view)



Description: A cross section view of the dielectric lens design produced by the Genetic Algorithm, utilizing a neural network fitness function trained on the 10,000-sample dataset. This lens is structured for improved performance in the more constrained design space, aiming to enhance the antenna's spectral content at 500 MHz. Despite geometric improvements, performance gains were modest compared to the best random designs.

- **Limited Improvement:** There was no significant improvement over successive generations, indicating stagnation in the optimization process.
- **Dependency on Neural Networks:** The GA's effectiveness was compromised due to the inaccuracies in the neural network predictions, which guided the selection and evolution of designs.

5. Discussion

5.1 Challenges and Limitations

The primary challenges encountered in the research were:

- **High Degrees of Freedom (DOF):** The lens geometry optimization problem involves a vast number of variables due to the fine resolution and extensive design boundaries of the lens. Even when considering a constant dielectric material (not varying the dielectric constant) and focusing solely on the input variables (presence or absence of material at each node), the DOF remains exceedingly high. With a grid resolution of 1 mm × 1 mm over a 15 mm (y) × 135 mm (z) area, there are approximately **2,025** nodes, each representing a binary decision. This results in $2^{2,025}$ possible configurations, creating a complex and expansive design space that is difficult to sample adequately with practical computational resources.
- **Insufficient Data Representation:** Despite generating over **10,000** samples, the dataset was insufficient to capture the full variability and complexity of the design space required for training accurate neural networks. The high DOF likely demands a significantly larger dataset to represent the search space effectively. Additionally, the uneven distribution of samples and potential gaps in the data further hindered the neural networks' ability to learn the underlying relationships between lens geometries and performance metrics.
- **Slow Data Collection Process:** Unusually, the process of generating the lens models was slower than running the simulations themselves. The MATLAB script used to create random lens geometries involved computationally intensive steps, particularly in visualizing and modeling the complex structures within CST Studio Suite. This bottleneck limited the rate of data collection. While full-wave electromagnetic simulations are inherently time-consuming, the model generation step became the primary constraint, reducing the overall efficiency of the data collection process.
- **Neural Network Limitations:** The models were unable to learn the complex, nonlinear mappings from lens geometry to performance metrics, likely due to the high DOF, limited data, and perhaps suboptimal network architectures. The regression task involved predicting performance metrics (FFT) over a wide output range (e.g., values ranging from 0 to 2×10^4), adding to the modeling challenge. The neural networks struggled to generalize from the training data to unseen configurations, leading to inaccurate predictions.

- **Software and Computational Constraints:** CST Studio Suite encountered difficulties handling the highly complex geometries produced by the genetic algorithm, often resulting in simulation failures. This necessitated a reduction in the search space and simplification of the models to ensure successful simulations. These constraints limited the exploration of more intricate designs that might have led to better performance, thereby restricting the potential of the optimization process.
- **Inefficient Data Generation Workflow:** The standard workflow involved generating lens geometries and running simulations within CST Studio Suite, which included visualization steps that slowed down the process. An alternative approach—generating the random lens STEP files directly in MATLAB and then loading them into CST for simulation—was identified but not fully implemented. By cutting out the visualization steps, this method could significantly increase the data collection rate, allowing for a more extensive dataset and potentially improving neural network training.

5.2 Implications

The limitations in the neural networks' predictive capabilities directly impacted the performance of the genetic algorithm. Since the GA relied on the neural network predictions to evaluate fitness, inaccuracies led to suboptimal selection and evolution of designs. The high DOF and insufficient data meant that the neural networks were not adequately trained to generalize across the expansive design space, resulting in unreliable fitness evaluations. Furthermore, the slow data collection process constrained the ability to gather additional samples that could enhance the neural networks' accuracy. The computational bottlenecks in model generation and the software limitations in handling complex geometries prevented the GA from exploring more diverse and potentially optimal designs. As a result, the GA failed to find designs that surpassed the best randomly generated lenses, indicating that the current approach may not be effective under the existing constraints.

6. Conclusions

The research aimed to optimize dielectric lenses for the 500 MHz biconical antenna by integrating neural networks and genetic algorithms to reduce computational costs and improve design quality. However, the approach did not yield the expected results due to several factors:

- **Inadequate Neural Network Performance:** The neural networks could not accurately predict antenna performance metrics from lens geometries, limiting their usefulness as surrogate models. The high degrees of freedom in the input space, combined with an insufficient and possibly inadequately diverse dataset, impeded the models' ability to learn the complex relationships necessary for reliable predictions.
- **Genetic Algorithm Limitations:** The GA's reliance on inaccurate neural network predictions led to ineffective optimization, failing to surpass existing design performances. Additionally, the GA tended to generate lens geometries that were too complex for CST Studio Suite to handle, causing simulation failures and necessitating a

reduction in the search space. This limitation curtailed the GA's ability to explore and identify optimal configurations within the broader design space.

- **High Problem Complexity and Computational Constraints:** The combination of high DOF and limited data made it challenging to model and optimize the lens designs effectively. The data collection process was hindered by the slow generation of lens models, which was paradoxically more time-consuming than running the simulations themselves. Potential methods to accelerate data collection, such as generating random lens STEP files directly in MATLAB and loading them into CST (thus bypassing computationally intensive visualization steps), were identified but not fully implemented. These constraints prevented the accumulation of a dataset large and diverse enough to train the neural networks effectively.
- **Software Limitations:** CST Studio Suite's difficulty in handling highly complex geometries produced by the GA further restricted the exploration of the design space. This limitation necessitated simplifying the lens models and reducing the search space, which may have excluded potentially superior designs that could enhance antenna performance at 500 MHz.

Overall, these challenges highlight that the current approach, under the existing constraints, may not be sufficient to achieve the desired optimization of dielectric lens designs for the 500 MHz biconical antenna. Addressing the high DOF, enhancing data collection methods, improving neural network architectures, and overcoming computational and software limitations are critical steps needed to advance this research.

7. Recommendations for Future Work

To overcome the challenges identified in this research and advance the optimization of dielectric lens designs for the 500 MHz biconical antenna, the following recommendations are proposed:

7.1 Enhance Data Collection Methods

- **Accelerate Model Generation:**
  - **Automate STEP File Creation:** Develop a method to generate random lens geometries directly as STEP files in MATLAB. By bypassing the visualization and complex modeling steps in CST Studio Suite, this approach can significantly reduce the time required to create models, allowing for faster data collection.
  - **Batch Processing:** Implement batch processing of simulations by preparing multiple lens models in advance and running simulations sequentially or in parallel, maximizing computational resource utilization.
- **Leverage High-Performance Computing:**

- **Parallel Simulations:** Utilize high-performance computing resources to run multiple full-wave electromagnetic simulations simultaneously. This can dramatically increase the number of samples collected within a given time frame.
- **Distributed Computing:** Explore cloud-based or distributed computing platforms to access additional computational power without significant infrastructure investment.

- **Increase Dataset Diversity and Size:**
  - **Adaptive Sampling:** Employ adaptive sampling techniques to focus data collection on regions of the design space that are underrepresented or exhibit high variability in performance metrics. This targeted approach can enhance the dataset's representativeness without requiring an exhaustive number of samples.
  - **Data Augmentation:** Apply geometric transformations to existing lens geometries to enrich the dataset without additional simulations. By introducing variations such as scaling, translation, rotation, or slight deformations within acceptable design limits, new valid samples can be generated. This enhances dataset diversity, improves neural network training, and aids the genetic algorithm in exploring the design space more effectively.

7.2 Reduce Problem Complexity

- **Simplify Lens Geometry:**
  - **Coarser Resolution:** Increase the grid resolution from 1 mm × 1 mm to a larger size (e.g., 2 mm × 2 mm or 5 mm × 5 mm) to reduce the number of nodes and, consequently, the degrees of freedom. This simplification can make the problem more tractable while still capturing essential geometric features.
  - **Parameterized Models:** Develop parameterized lens models with a reduced set of design variables. By defining the lens geometry using a smaller number of parameters (e.g., polynomial curves or spline functions), the complexity of the optimization problem can be significantly decreased.
- **Feature Engineering:**
  - **Identify Key Features:** Analyze the dataset to identify which regions of the lens geometry have the most significant impact on performance metrics. Focus on these critical areas to reduce the number of input variables.
  - **Dimensionality Reduction Techniques:** Apply methods such as Principal Component Analysis (PCA) to reduce the dimensionality of the input space, retaining the most informative features for the neural network models.

7.3 Improve Neural Network Architectures

- **Advanced Modeling Techniques:**

- **Convolutional Neural Networks (CNNs):** Utilize CNNs to exploit spatial correlations in the lens geometries. CNNs are well-suited for grid-like data and can reduce the number of parameters compared to fully connected networks, improving learning efficiency.
- **Autoencoders:** Implement autoencoders for unsupervised learning of efficient codings of the input data, which can help in capturing essential features and reducing dimensionality.

- **Hyperparameter Optimization:**
  - **Automated Tuning:** Use automated hyperparameter optimization tools (e.g., grid search, random search, Bayesian optimization) to systematically explore combinations of neural network hyperparameters for optimal performance.
  - **Regularization Techniques:** Incorporate advanced regularization methods such as dropout, batch normalization, and L1/L2 regularization to prevent overfitting and improve generalization.
- **Cross-Validation and Model Evaluation:**
  - **Robust Validation Methods:** Implement k-fold cross-validation to assess the model's ability to generalize to unseen data, ensuring that the neural networks are not overfitting to the training set.
  - **Ensemble Methods:** Explore ensemble learning techniques by combining predictions from multiple models to improve overall performance and reduce variance.

7.4 Explore Alternative Optimization Strategies

- **Hybrid Optimization Algorithms:**
  - **Combine GA with Other Methods:** Integrate the genetic algorithm with optimization methods such as Particle Swarm Optimization (PSO), Differential Evolution (DE), or Simulated Annealing (SA) to leverage their complementary strengths.
  - **Multi-Objective Optimization:** Formulate the optimization problem as a multi-objective task, considering trade-offs between different performance metrics (e.g., maximizing electric field intensity in frequency and time domain).
- **Surrogate-Assisted Optimization:**
  - **Alternative Surrogate Models:** Experiment with other surrogate modeling techniques such as Gaussian Processes, Support Vector Regression (SVR), or Random Forests, which may offer better predictive performance for certain types of data.

- **Active Learning:** Use active learning strategies to selectively query simulations for the most informative lens designs, improving the surrogate model iteratively.

7.5 Address Software and Computational Constraints

- **Optimize Simulation Workflow:**
  - **Script Automation:** Enhance automation scripts to minimize manual intervention and reduce errors during model generation and simulation setup.
- **Alternative Simulation Tools:**
  - **Explore Other Software Options:** Investigate the use of alternative electromagnetic simulation tools that may handle complex geometries more efficiently or offer faster simulation times.
  - **Model Order Reduction:** Employ techniques to reduce the computational complexity of simulations, such as using simplified physics models or lower-fidelity simulations for preliminary evaluations.

7.6 Collaboration and Interdisciplinary Approaches

- **Engage with Domain Experts:**
  - **Antenna Engineers:** Collaborate with antenna design experts to gain insights into critical design factors and practical constraints, aiding in feature selection and model simplification.
  - **Machine Learning Specialists:** Work with data scientists to explore advanced modeling techniques and optimization algorithms.
- **Cross-Disciplinary Research:**
  - **Applied Mathematics:** Leverage expertise in optimization theory and computational methods to develop more efficient algorithms.

8. Final Remarks

This research endeavored to optimize dielectric lens designs for a high pulse-powered biconical antenna operating at 500 MHz by integrating neural networks and genetic algorithms. While the initial approach faced significant challenges and did not yield the expected results, valuable insights were gained that can inform future efforts in this domain.

The high degrees of freedom inherent in the lens geometry optimization problem, coupled with computational and software constraints, underscored the complexity of applying machine learning and evolutionary algorithms to such tasks. The limitations in data collection and neural network performance highlighted the need for more efficient data generation methods and advanced modeling techniques.

Despite the setbacks, the integration of neural networks and genetic algorithms remains a promising avenue for antenna design optimization. By addressing the identified challenges through the above strategies—enhancing data collection, reducing problem complexity, improving neural network architectures, exploring alternative optimization methods, and overcoming computational constraints—there is potential to realize significant advancements.

Future work that implements these recommendations may overcome current limitations, leading to the discovery of novel lens geometries that enhance antenna performance at the desired operational frequency. Such advancements would contribute to the broader field of electromagnetic design optimization, demonstrating the viability of combining machine learning with evolutionary strategies in engineering applications.

In conclusion, while the current approach did not achieve the desired optimization outcomes, the research provided critical understanding of the complexities involved and set the stage for more effective methodologies. Continued efforts, interdisciplinary collaboration, and innovation in both computational techniques and theoretical frameworks are essential to advance the optimization of dielectric lenses and, by extension, the performance of high-frequency antennas.

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Continued collaboration and interdisciplinary engagement are vital as we strive to overcome the obstacles identified and achieve the desired advancements in antenna design. We remain committed to pushing the boundaries of what is possible through innovative research and development.