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Performances Evaluation of Machine Learning Optimization in the Electromagnetic Design of a Metamaterial-Inspired Patch Antenna

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Abstract

This paper explores the application of machine learning techniques to optimize the design of a metamaterial-inspired patch antenna. Specifically, the miniaturization of a circular microstrip antenna, is enhanced through AI-driven optimization. Key design parameters are optimized to reduce antenna size while maintaining adequate reflection coefficient values. By exploiting machine learning, the proposed approach enables a significant reduction in computational cost compared to traditional full-wave analysis while preserving design accuracy. The results highlight AI's potential in accelerating the antenna design process and demonstrate its broader applicability in electromagnetic simulations and optimization.

1. Introduction

In recent years, artificial intelligence has profoundly transformed various fields of science and engineering, including the analysis of electromagnetic systems [1]-[3].
Machine learning-based analysis, a subset of AI, offers significant advantages over traditional methods like full-wave analysis. These include reduced computation times, as trained models can generate predictions almost instantaneously, and enhanced efficiency, enabling the rapid exploration of complex design spaces and the evaluation of numerous potential solutions in a short timeframe. Furthermore, machine learning models exhibit remarkable scalability, adapting easily to systems of varying sizes and to problems of diverse nature.
In this contribution, we exploit the potential of Machine Learning techniques to optimize the design of a metamaterial-inspired patch antenna. In particular, as a case study, we consider a circular microstrip antenna loaded by a Complementary Split Ring Resonator (CSRR) [4]. The antenna geometry, shown in Figure 1, is optimized by varying the number of complementary split rings, the radius of the largest ring, the width of the slots, the width of the metallization, and the width of the gaps. To reduce optimization costs, the values of the width of the slots metallization and gap are kept the same for all split-rings, while the disk radius is fixed before optimization. The goal is to reduce the size of the antenna while maintaining adequate radiation efficiency.
The chosen operating frequency for the antennas is 2.5 GHz, a widely used frequency in telecommunications and wireless systems [5]-[7]. It plays a pivotal role in technologies such as Wi-Fi networks, Bluetooth for short-range communication, mobile communication systems like LTE, radar, environmental monitoring sensors, and high-definition wireless video transmission. This focus underscores the relevance of AI-driven advancements in addressing the growing demands of modern communication and sensing technologies [8]-[10].
Full-wave analysis, which solves Maxwell's equations, is extremely accurate but requires considerable computational resources. In contrast, the AI-based approach, using machine learning, offers a faster and more efficient solution, allowing to explore numerous design configurations in a short time. The contribution highlights how AI can accelerate the antenna design and optimization process, while maintaining a level of accuracy adequate for many practical applications, and serves as a bridge towards the integration of AI techniques in electromagnetic design.

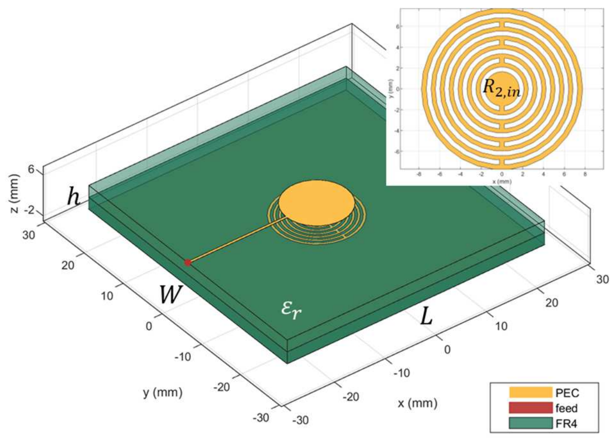

Figure 1. The antenna design with parameters used in the AI code.

2. Antenna AI Analysis

A key aspect of the AI analysis is its ability to automatically optimize the design space. In the antenna modelling process, the identification of key design parameters, such as length, width and height of the substrate, is crucial. Here, the AI-based code explores different combinations of lengths and widths for the

selected antenna, creating a matrix that represents the resonant frequencies for each geometric configuration.
Different random antenna configurations are generated and the electromagnetic performance of each configuration is then simulated with full-wave techniques. The data obtained is then pre-processed and used to train the machine learning model, which is then used to train a regression model able to predict the resonant frequency (f_R) of the antenna, thus allowing to improve the performance and design of the antenna based on the physical parameters.
In particular, the process starts with the definition and parameterization of the antenna structure. The six main parameters are: length (L), width (W), fixed radius (r), substrate height (h), relative permittivity (ε_r) and number of slots (N). An additional parameter, the internal radius of the CSRR ($R_{2,in}$), completes the geometric definition. These independent variables, called predictors, represent the antenna design parameters that the machine learning model uses to make the predictions, while the dependent variable, called response, is the antenna characteristic that is to be predicted. These parameters define the physical and geometric properties of the antenna, influencing its electromagnetic behaviour. Each combination of these parameters generates a unique configuration of the antenna. In our case, the variable that the model predicts is the resonant frequency of the antenna.

3. AI Training

In this section we preliminary demonstrate how integrating machine learning techniques can accelerate the design process of an antenna without compromising its accuracy.
The parallel coordinate plot of Figure 2 illustrates the relationship between the antenna design parameters and the resonant frequency, providing a visual representation of how design choices influence performance. Each coloured line represents a specific antenna configuration, for example a line could represent a configuration with $L = 50, W = 40, \varepsilon_r = 4.4,\ N = 7,\ R_{2,in} = 0.35$, and so on, finally showing the achieved resonant frequency f_R.
The legend on the right side of the graph further enhances this understanding, helping to visually distinguish configurations with similar resonant frequencies. It is important to note that, within each colour range, multiple f_R values can be present, meaning that different configurations may exhibit distinct resonant frequencies while still falling within the same general range identified by the color. For instance, the blue lines represent configurations with low resonant frequencies, between 1.2 and 1.37 GHz, while the red and orange lines indicate higher frequencies. If the graph shows lines that frequently cross the variable axes, this may indicate a complex relationship between those design parameters, suggesting that there is no simple linear correlation between those parameters and the f_R response. The variables may therefore interact with each other in a nonlinear manner, affecting the resonant frequency in complex ways. The graph can be used to identify configurations that maximize or minimize the resonant frequency based on changes in the design parameters. For example, by observing the colour changes across the axes, one can infer the impact of different parameters on the resonance frequency. If a sharp change in colour of the lines from one axis to the other is observed, this could suggest that that particular variable has a significant influence on the resonant frequency. This type of information is valuable for optimizing antenna performance, since it allows to better understand the role of each parameter in determining the final response. For each parameter configuration, the reflection coefficients, obtained by full wave simulations, have been plotted to verify that every combination has a valid physical interpretation (Figure 3).

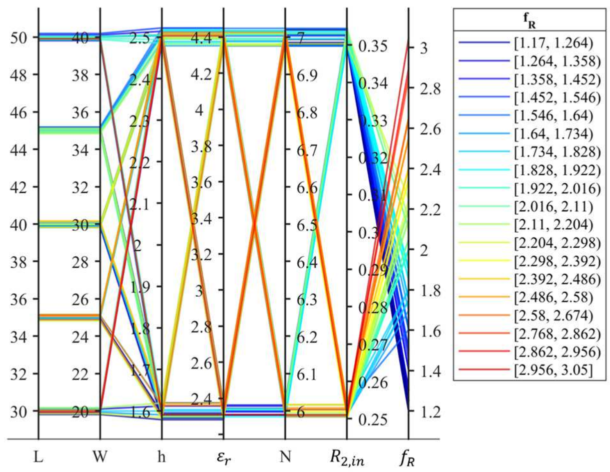

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Figure 2. Parallel coordinate plot showing the relationship between antenna design parameters and resonant frequency. Crossing lines on the axes highlight complex relationships between parameters.

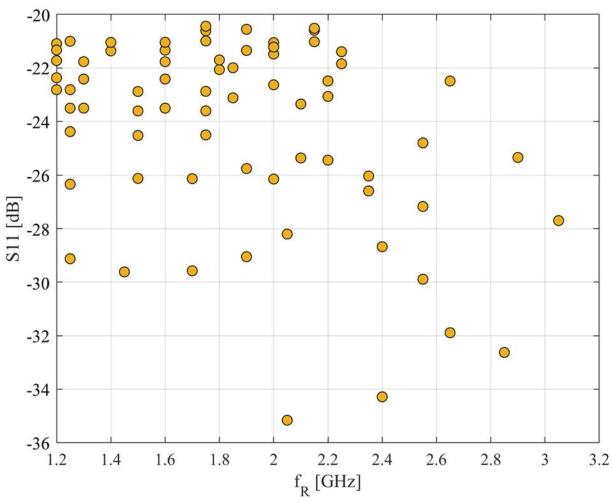

Figure 3. Validation of the $|S_{11}|$ for each configuration of Figure 2.

4. AI Optimization Results

Once the code training was completed, as discussed in the previous section, and the model was trained to accept only values with electromagnetically valid S_{11} results, the actual optimization process could begin. The objective is to design a patch antenna with a CSRR, starting exclusively from the target resonant frequency, without relying on predefined design parameters. In this case, the chosen frequency is 2.5 GHz, which was not included in the original training dataset. As a result, the model does not have prior knowledge of any antenna configurations corresponding to this specific frequency, making this a true test of its generalization capability. The ability to generate a viable antenna design for an unseen frequency demonstrates the effectiveness of the trained model in exploring new design spaces. The result presented in the following figures, therefore, represents a distinct case compared to those used during training, highlighting the model's ability to extrapolate beyond the data it was originally exposed to.

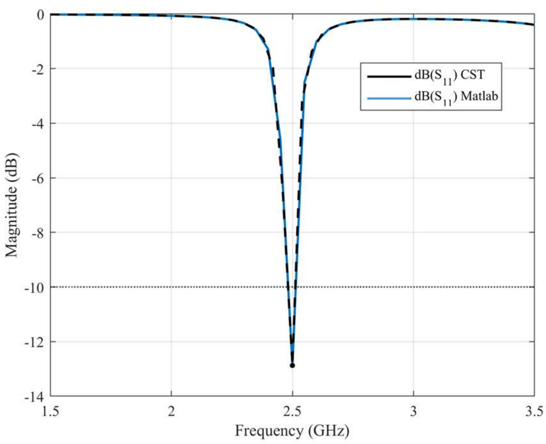

Figure 4. The S11 of the patch CSRR antenna designed with the AI optimization and simulated with Matlab and CST microwave studio.

According to the AI-generated results, the optimal patch antenna design for a resonant frequency of 2.5 GHz should have the following parameter values: $L = 50mm$, $W = 50mm$, $h = 2.3mm$, $\varepsilon_r = 4.8$, $N = 7$, $R_{2,in} = 0.3521mm$. Once these geometrical parameters were determined, full-wave simulations of the complete structure were performed to validate the AI's predictions. Figure 4 presents a comparison between the antenna simulation results obtained using MATLAB and CST, highlighting the consistency between the two methods. While, Figure 5 illustrates the radiation pattern, along with a cross-sectional view of the gain distribution along the vertical plane. The maximum gain is 3.2 dB. Finally, Figure 6 shows the input impedance of the designed antenna, providing further insights into its performance. These results serve to validate the AI-driven design process by confirming that the predicted parameters lead to an electromagnetically antenna configuration with good performances.

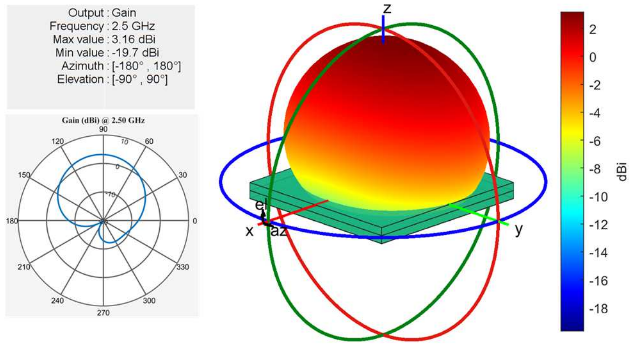

Figure 5. Radiation pattern of the designed patch antenna at 2.5 GHz, including the directivity section along the vertical plane.

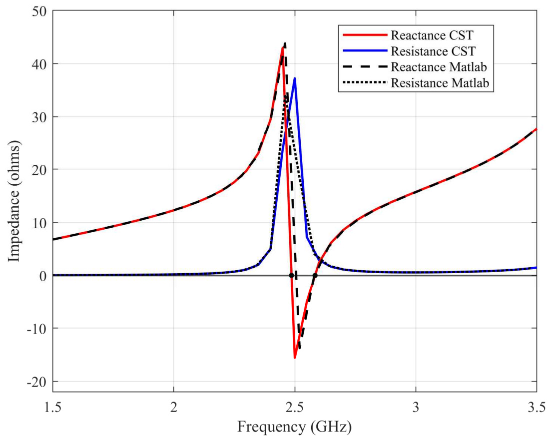

Figure 6. Comparison of the impedance response obtained from full-wave simulations using CST and MATLAB for the designed antenna at 2.5 GHz.

5. Conclusions

In this contribution, we have shown that the AI-based approach represents an effective and fast alternative to full-wave methods for antenna design and optimization. The results show that, although not reaching the absolute accuracy of full-wave analysis, AI techniques provide predictions that are accurate enough for preliminary design steps, with the great advantage of significantly reducing computation times to perform the simulation. The code not only optimizes the antenna geometries, but also allows to explore how variations in the parameters affect the performance, without having to run complex electromagnetic simulations. Although AI simulations do not reach the absolute accuracy of full-wave simulations, they offer a favourable compromise for applications where computational speed is essential. In conclusion, the integration of artificial intelligence techniques in electromagnetic antenna design opens new perspectives to improve the efficiency and speed of simulations, paving the way for new applications and possibilities in the field of design of antennas and complex electromagnetic devices.

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