Machine learning-based theoretical optimization of antenna design

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Abstract: The changing communication era demands higher precision and more efficient antenna designs, which require more automated processing methods and more powerful data storage techniques. Currently, machine learning can optimize solutions at high speed and has shown powerful performance in various fields, attracting much attention. This paper summarizes the application of machine learning in antenna design, analyzing its basic concepts and relationship with artificial intelligence and neural networks. This paper also compares the methods and effects produced in each application by analyzing the results of electromagnetic characteristic curves. The results show that machine learning reduces computational errors and computation time and is able to predict the next input and correct the antenna behavior with high accuracy. The key outcomes are quickening the antenna design procedure, decreased mistakes, and wasted time, and increased antenna design accuracy. Machine learning algorithms can assist antenna design in the future to improve antenna accuracy and design efficiency.

Keywords: Antenna Design, Machine Learning (ML), Neural Networks (NN)， Electromagnetic Properties.

1. Introduction

In the 21st century, with the advent of the 5G era, wireless communication technology has gained more and more attention from the public, and antenna design is crucial in communication. Researchers contributes to optimize antenna design ideas and design more efficient, wider applications and directional high gain antennas, including but not limited to developing novel feed structures, changing the number of antennas and array size and antenna arrangement [1][2], adjusting the antenna polarization [3] or replacing specific elements [4], etc. However, most of the aforementioned conventional antenna design methods are related to changing the geometrical characteristics to find the optimal state for a specific frequency band. This process requires several attempts to analyze and adjust, which takes a long time and great effort.

In recent years, machine learning techniques have become mature and are used in many fields, such as image processing, medical [5], stock market analysis, information filtering, automatic cruising, etc. However, compared to these fields, machine learning has been relatively less applied in antenna design and electromagnetics, probably because the design process mostly relies on the researchers' skills, and it is difficult to translate the skills and experience into machine language for machines to perform. More importantly, most of the design work requires the joint participation of multiple companies and departments to design different components separately and finally assemble them into antennas where the components match each other and meet the standards. It is easy to see that the adaptability of the components and the mastery of the objectives of the end device are not simple for machine learning engines.

The goal of this study is to build artificial intelligence to give practical data analysis in accordance with design requirements. It does this by analyzing the optimization degree of antenna design using various machine learning techniques. In this study, the classification of machine learning algorithms will be summarized based on an overview of the field. The relationship between machine learning, artificial intelligence, and deep learning will also be sorted out, and common machine learning algorithms like neural networks, linear regression, and random forests will be introduced. Among these, Radial basis functions (RBFs) and Support Vector Machines (SVMs) are introduced. Finally, by examining the individual machine learning applications in antenna design and examining the electromagnetic properties of each method employed, this research provides a concise summary of the function of machine learning in antenna design. The list provides a unifying explanation of it.

2. Theoretical Analysis of Machine Learning

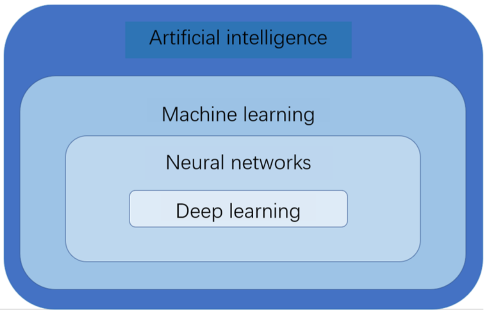

Figure 1. the relationship between artificial intelligence, machine learning, neural networks, and deep learning

The core of artificial intelligence is to simulate human thinking patterns with machines. As shown in Figure 1, machine learning is at the heart of the field of artificial intelligence. An easy-to-understand definition of machine learning is that the performance P of a computer program on processing a task T can improve with the accumulation of learning experience E, as shown in Figure 2.

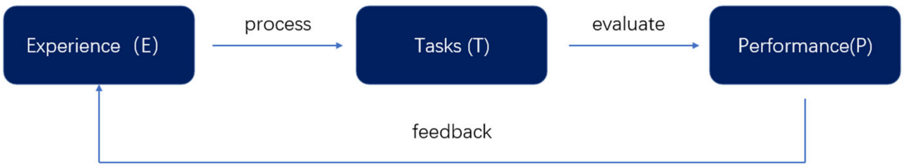

Figure 2. Definition of Machine Learning

Research in machine learning aims to enable computers to learn, to be able to simulate human learning behavior, build learning capabilities, and achieve recognition and judgment. The most basic machine learning approach is to use algorithms to parse large amounts of data, find patterns in them, and use the learned thinking models to make decisions and predictions about real events. Machine learning has four important elements: data, models, learning objectives, and optimization algorithms. This paper mainly explains the last three.

As shown in Figure 3, learning from a data sample $(x, (y))$ and optimizing the model parameters w to adjust the effective representation of each feature eventually leads to a decision function $f(x, w)$, which serves to map the input variable x to the output prediction Y under the action of the parameters w.

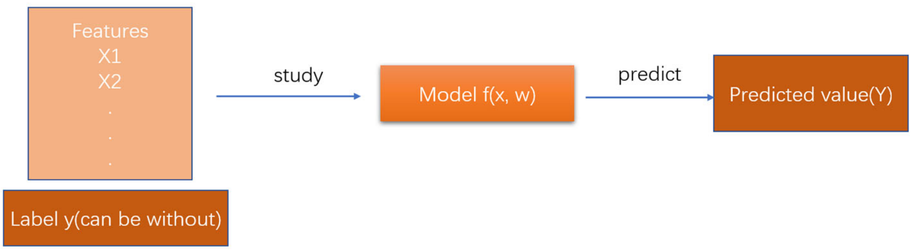

Figure 3. Machine Learning Model

Different loss functions are required to measure various task goals. For functional assurance, the loss function ought to be modest and the error between the model's anticipated and actual values must be as little as feasible. The two main ones are as follows.

The mean square error (MSE) loss function is highly recommended when measuring the model regression prediction error profile. The formula is shown below:

$$J(w) = \frac{1}{m}\sum_{i=1}^{m}\left(y^{(i)} - f\left(x^{(i)}, w\right)\right)^2 \tag{1}$$

When measuring the error profile of a classification prediction model, the cross-entropy loss function derived from the great likelihood estimation method is commonly used. By minimizing the cross-entropy loss, the model prediction distribution is made to be as consistent as possible with the empirical distribution of the actual data. The formula is:

$$J(w) = \frac{-1}{m}\sum_{i=1}^{m}\left[y^{(i)}\ln\left(f\left(x^{(i)}, w\right)\right) + \left(1 - y^{(i)}\right)\ln\left(f\left(x^{(i)}, w\right)\right)\right] \tag{2}$$

The optimization algorithm's goal is to improve the parameter values by iteratively modifying the model's parameters over a limited number of times in order to minimize the loss function's value. The commonly used algorithm is the gradient descent algorithm, and this process can be understood figuratively as the process of descending a mountain and finding the lowest footing, as shown in Figure 4. The algorithm steps are shown in Figure 5.

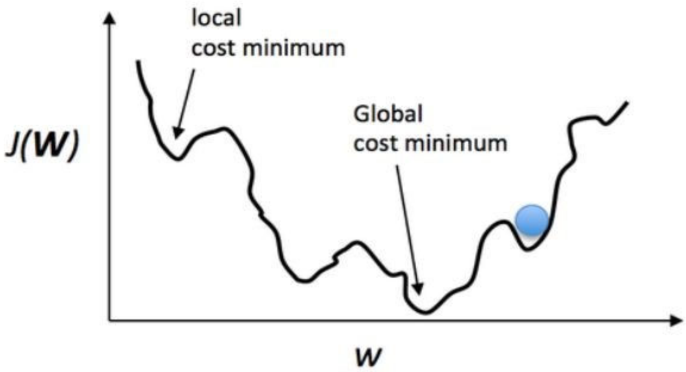

Figure 4. Loss function

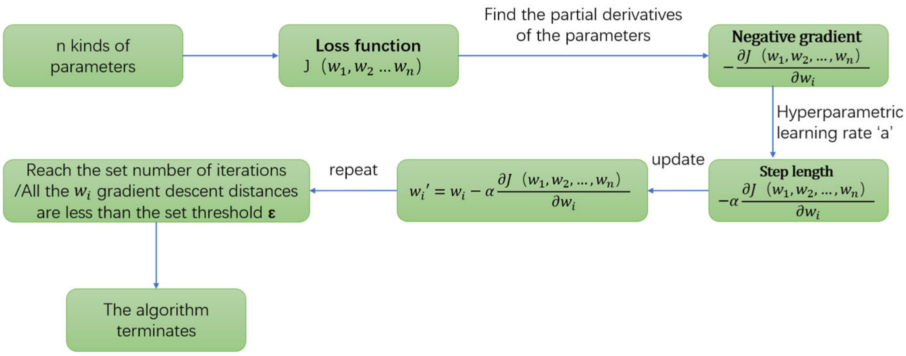

Figure 5. Steps of gradient descent algorithm

Machine learning algorithms can be broadly classified into supervised, unsupervised [6] and reinforcement. The categories and algorithm characteristics are shown in Table 1.

Table 1. Three main categories of machine learning

Categories	Features
Supervised algorithms	● A learning model is built according to the training dataset. ● Requires specific inputs and outputs [6]. ● Include artificial neural network [7], linear regression, support vector machines [8], decision tree, random forest, etc.
Unsupervised algorithms	● No specific target output. ● divides data into different groups [6]. ● The main algorithms include k-means, dimensional reduction.
Reinforcement algorithms	● Decision-based training: based on the accuracy of the output. ● Give the predictions. ● Stimulated by rewards and punishments, form expectations, produces habitual behaviors, and maximize benefits.

This paper presents the main machine learning algorithms and neural network models applied in the current antenna design field. An overview of the algorithms is given in Table 2.

Table 2. Three main categories of machine learning

Name	Traits	Principle	Application
Random forest	● The sets of decision trees.	● Estimate the categories ● Choose the category with the most votes.	● Regression prediction ● Data downscaling.
DCN	● Deep learning with more than two hidden layers.	● Create smaller input scan layers that slide over the original image ● Transfer to the convolution layer [9].	● Image Recognition processing.
SVM	● Data classification.	● Plot the data ● Find the optimal divider.	● Character recognition. ● Facial recognition. ● Wireless communication [11]. ● Text classification.
ELM [10]	● Fast running speed.	● Set weights ● Train with least squares fit.	● Image resolution improvement ● Wind prediction.
RBF	● Faster learning speed ● General approximation capabilities.	● Output 0 and 1 ● Determine the answer as yes or no,	● Nonlinear function approximation, ● Control and fault diagnosis [12].

3. Machine learning in antenna design

The adoption of machine learning in antenna design applications is steadily growing. The research idea of designing antennas by machine learning can be summarized in Figure 6.

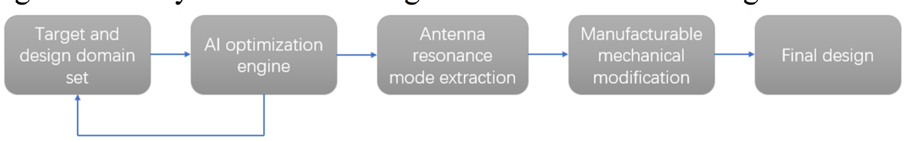

Figure 6. Steps to design antennas by machine learning

3.1. Random Forest-based method

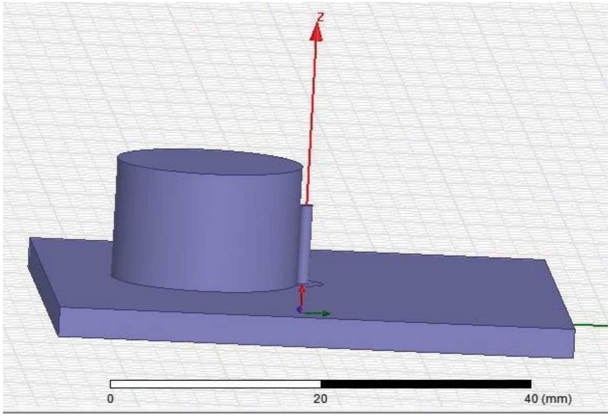

Figure 7. Simulated Antenna

As shown in Figure 7, the researchers constructed a dielectric resonator antenna (DRA) consisting of ceramic materials of different shapes, aiming to improve the antenna parameters to improve the performance and gain of the antenna. It has been shown in previous studies that Gaussian Process Regression (GPR) is effective in aiding antenna modeling, but further improvements in accuracy can be made. Therefore, in this study, researchers use the random forest algorithm for a comparative study of antenna performance.

The deep neural network architecture used in this study has four hidden layers. Using the aforementioned gradient descent approach, which is a hyperparameter that modifies the network weights in accordance with the loss function, it improves the learning rate. Finally, MSE is used in this work as a statistic to assess the model quality. Table 3 is a list of the mean squared errors for each model.

Table 3. MSE values for different models

	Model	**MSE values**
1	GPR	5.595727
2	Random forest(normal)	0.433456
3	Random forest (Hyper Parameter Tuning)	0.172102

The MSE values of random forest are significantly reduced compared to the GPR algorithm in [12]. There is a further reduction by additional hyperparameter tuning operations, indicating that a more accurate model is obtained, proving the significant role of random forest in parameter tuning.

In the next step, the researcher simulated the antenna using HFSS software from Ansys and compared it with the model that used a random forest and neural network. As shown in Figure 8, by comparing the S_{11}(dB) of the three different models, we can conclude that the neural network pattern is very similar to the software simulated pattern when the predicted values are within the range of the input data points, while the random forest pattern has the best S_{11} parameter characteristics below -10 dB around 7Ghz, meaning that it has the least reflection and the best performance.

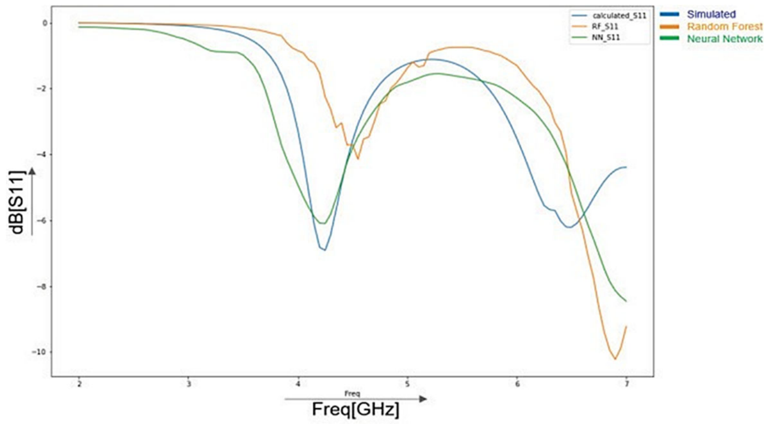

Figure 8. S_{11} parameters for different models

3.2. SVM-based method

An example of an SVM algorithm is optimization using the least squares SVM (LS-SVM). By applying the equation Lagrangian in [13], the material properties and loading of the substrate are changed to reconfigure the array, maintaining the beam formation and beam steering of the array. At the same time, the algorithm allows the maintenance of the unexpected failure of the antenna array elements. The problems related to the direction of arrival (DOA) are also solved.

This study's LS-SVM algorithm is trained using the covariance matrix method [29]. It can be trained to analyze the variation of the environment (platform, terrain, etc.) in which the antenna is located, taking into account factors such as the number and spacing of the antenna elements. Figure 9 shows the results of DOA evaluation using LS-SVM and compares it with the DOA estimation algorithm using regression-based Multiple Signal Classification (MUSIC).

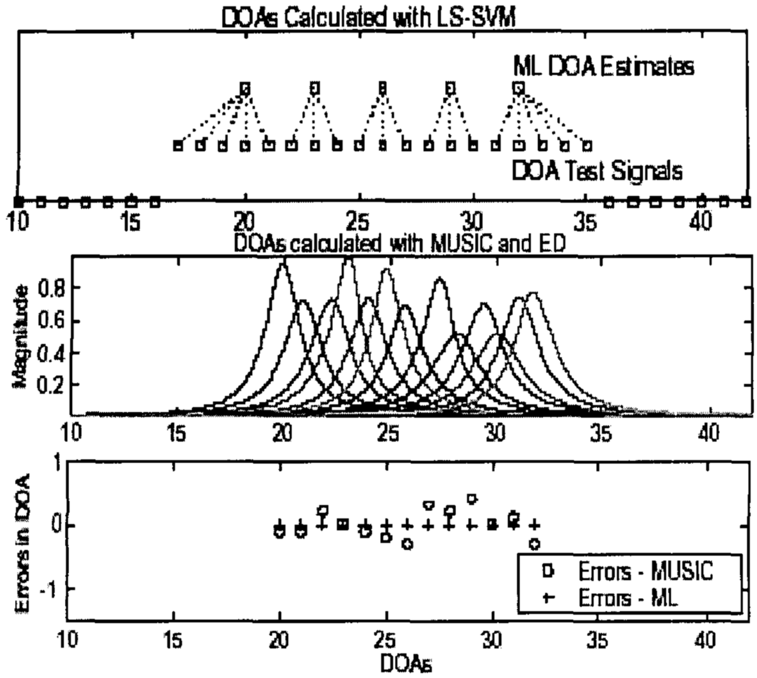

Figure 9. DOA estimation results using MUSIC and LS-SVM algorithms

Both algorithms can predict the incoming arrival wave angle (pitch and azimuth). In contrast, the DOA estimation by LS-SVM optimization algorithm will be more accurate, allowing the radar antenna array to maintain normal operation even when individual components fail or the surrounding environment changes. This is of great help in radar signal processing.

The CNN algorithm was compared with the MUSIC algorithm in solving the DOA estimation problem in [14]. It was concluded that the CNN algorithm performs as well as the MUSIC algorithm and performs robustly in the signal-to-noise ratio, again providing valuable ideas for solving the DOA problem, which will not be repeated here.

The use of the SVM algorithm to accelerate the design of shaped beam reflect array unit cell is also presented in [15]. Although the Method of Moments (MoM-LP) algorithm has been proven to have good results, there is room for improvement in computational speed. In this study, the two algorithms are compared using four parallel dipole models in Figure 10, which characterize the reflection coefficient matrix and derive the scattering parameters for the unit cell size, taking into account the discretization of the incident angle.

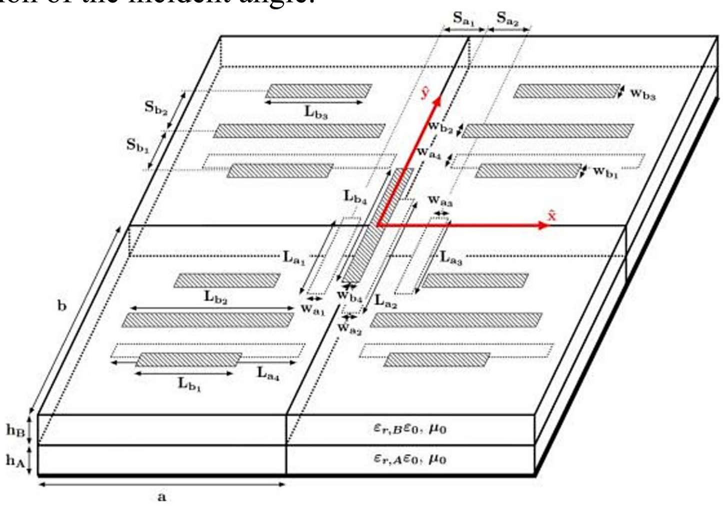

Figure 10. The model of reflect array unit cell

Figure 11 shows the gains of the two algorithms for each incidence angle case. The results show that using SVM can speed up sequential and parallel designs by 880 and 556, respectively.

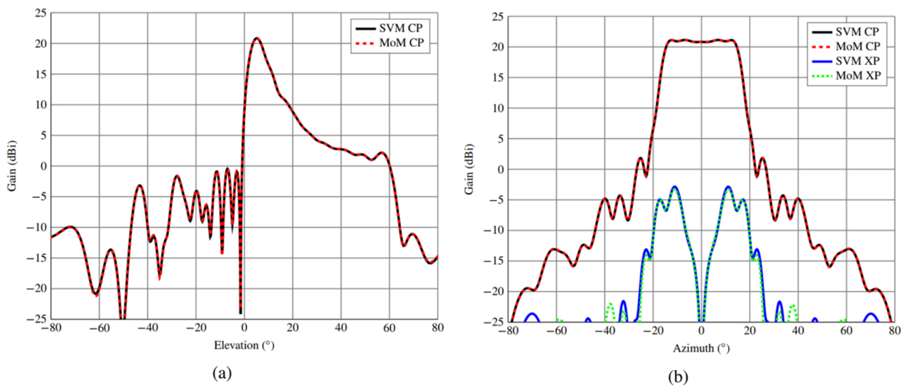

Figure 11. Gain comparison of SVM and MoM-LP

3.3. ELM-based method

It is crucial to find the complex array components early on. [29] mentions the application of the LS-SVM algorithm to deal with unforeseen antenna array breakdowns. Otherwise, the malfunctioning antenna component might ruin the array's antenna's geometric distribution. As a result, there will be several issues, including beam pattern distortion, gain decrease, initial null beamwidth, half-power beamwidth, and an increase in the array's edge flap level. Thus, the array system's performance would be significantly decreased. As a result, the researchers need to training the ELM algorithm using optimum antenna array configurations. It learns to identify the quantity and position of defective components from the observed antenna array patterns by being given models of various component failures.

In this study, the ideal array's elements' amplitude and phase errors in the excitation channel are increased using the formula to imitate the observed pattern.

$$F(\theta) = \sum_{i=0}^{N-1} I_i \cdot (1+\delta_i) \cdot l_i \cdot e^{\left(j \cdot \frac{2\pi}{\lambda} x_i \sin\theta + \Delta\theta_i\right)} \tag{3}$$

The ideal and measured patterns are shown in Figure 12(a), and the measured phase and amplitude errors are 5° and 0.5 dB, respectively.

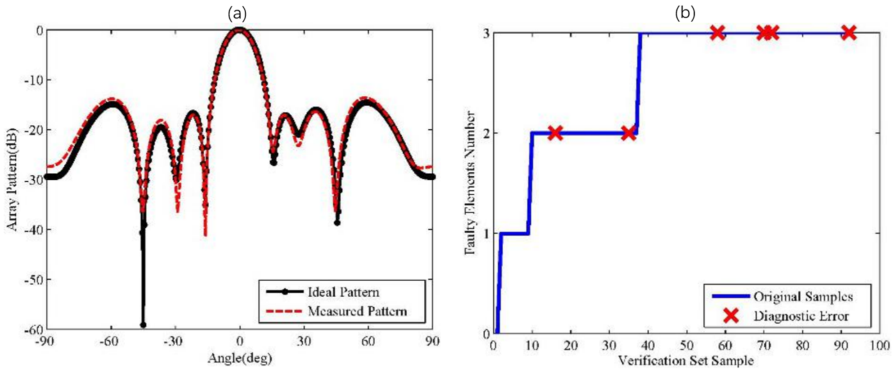

Figure 12. (a)Errors of the patterns. (b)Diagnostic results of ELM

The researchers introduced a prepared sample of the array radiogram, including the defective cells into the trained ELM network after training it with the radiogram pattern of the array. The defective cells' number and position may be mapped from the array using the network's output of encoding the array's cell locations. It is possible to determine the network's accuracy in identifying defective units by comparing the output to the actual output. This way, it is possible to assess the ELM's accuracy in identifying malfunctioning array units. Figure 12(b) displays the problematic element diagnosis findings. The results indicate that the majority of defective samples may be found.

Consequently, it is possible to identify defective antenna array components using the ELM network. The development of the study revealed that by expanding the network's hidden layer nodes, the stability and accuracy of detection might be enhanced. Patch antenna arrays can also employ the methodology.

3.4 RBF-based method

Figure 15 depicts the fractal antenna design. This work applies a tiny hexagonal fractal unit to each corner of the hexagonal radiator of a monopole antenna supplied by a coplanar waveguide (CPW). To determine the degree of generalization possible, radial basis function (RBF) and least squared regression (LSR) methods were used to forecast the S 11 and gain response of this antenna.

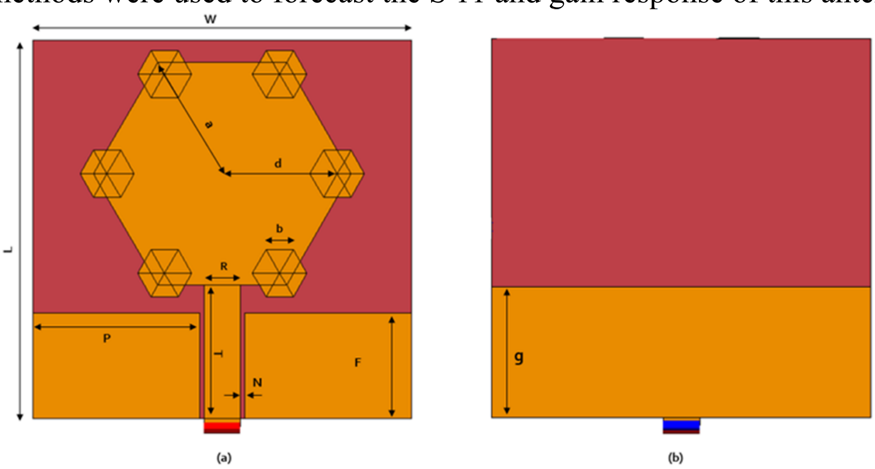

Figure 13. Geometry of the model (a) Top view (b) Bottom view

The researchers trained two ML models with the top four of the 11 variables shown in Figure 13: the radius of the hexagonal patch a, the radius of the fractal cell b, the distance between the center of the fractal cell and the center of the hexagonal patch d, and the gap N between the feeder and the plane perpendicular to the bottom. Test inputs of the trained ML models were used outside the data set used for training to verify that the models could correctly make predictions. The prediction accuracy with machine learning was verified by comparing it to the FEKO response shown in Figure 14.

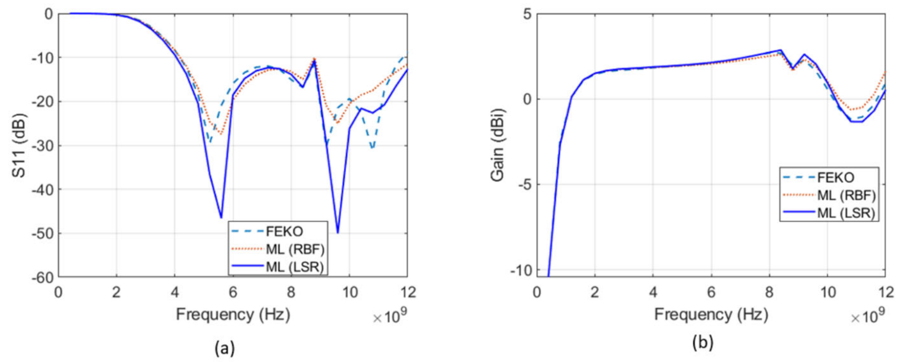

Figure 14. (a) S11 and (b) Gain from FEKO, RBF and LSR.

The replies utilizing FEKO and the anticipated output from RBF and LSR are extremely similar, with RBF having a greater accuracy and better generalization than LSR. Table IV displays the amount of time and memory used by the ML algorithm and FEKO to plot the produced patterns. The antenna response prediction can be performed with less time and memory using the ML algorithm. Finally, Table V provides a summary of instances of machine learning methods used in antenna design.

Table IV: Comparison of time and memory required

Method	FEKO	RBF and LSR
time	18mins	<5 seconds
memory	33MB	<4 KB

Table V: Comparison of machine learning algorithms in citations

Application object	Research purpose	Algorithm	Compared to	Advantages
Dielectric resonator antenna (DRA)	Adjust parameters to improve performance	Random forest	GPR	Higher accuracy and better antenna performance
Array	DOA/Auxiliary design	SVM	MUSIC/mom	Improve design efficiency and maintain high precision.
Array	DOA	CNN	MUSIC	More robust to signal-to-noise ratio changes.
Array	Detection of failure unit	ELM		Stable and accurate
Fractal Antenna	Antenna Response Prediction	RBF	LSR	Better generalization ability and higher accuracy

It can be seen that machine learning algorithms provide a great help in antenna design. In practical applications, machine learning provides researchers with great convenience and selectivity. Researchers can use a variety of suitable algorithms to achieve the same purpose, while different algorithms have unique advantages in different fields. From the perspective of parameter optimization, researchers can train algorithms such as SVM to optimize the parameters of antennas by using data from training sets and find approximate solutions to optimization problems to prevent or solve equipment failures.

4. Conclusion

This paper describes the relationship between machine learning and artificial intelligence and deep learning, popularizing the concept of important machine learning algorithms and examples of their application in antenna design. The numerous advantages of machine learning algorithms are highlighted by comparing them with ordinary antenna design. The main effects are to speed up the antenna design process, reduce errors and time consumed, improve the accuracy of antenna design, help researchers save a lot of simulation work, and propose approximate solutions to specific optimization problems.

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