APPLYING MACHINE LEARNING TO THE PREDICTION OF OUTPUT PARAMETERS IN ANTENNA DESIGN

ỨNG DỤNG HỌC MÁY TRONG DỰ ĐOÁN CÁC THÔNG SỐ ĐẦU RA CỦA THIẾT KẾ ANTEN

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Abstract:

This paper presents the application of machine learning (ML) to predict and optimize parameters in antenna design. The main contribution of the paper is using a ML model with training and evaluation dataset as parameters obtained from antenna simulation results by CST software. The results of the model are used to predict antenna dimensions at the desired resonant frequency. In this paper, the K-Nearest Neighbors (KNN) algorithm is applied to predict the parameters of the antenna patch. The accuracy of the prediction results is evaluated and analyzed using root mean square error (RMSE). These results can provide a basis and new direction to improve the antenna design process, contributing to progress in deploying more modern and efficient wireless systems. The prediction results contribute to reducing the time to optimize parameters in the antenna design.

Keywords:

Machine Learning in Antenna, AI in Antenna, Antenna Parameter Prediction, Antenna Patch.

Tóm tắt:

Bài báo này trình bày việc ứng dụng học máy (ML) để dự đoán và tối ưu các tham số trong quá trình thiết kế anten. Bài báo sử dụng tập dữ liệu thu được từ kết quả mô phỏng anten bằng phần mềm CST để huấn luyện và đánh giá mô hình. Mô hình được sử dụng để dự đoán các kích thước của anten hoạt động ở tần số mong muốn. Trong bài báo này, thuật toán KNN được ứng dụng để dự đoán các thông số của anten patch. Độ chính xác của kết quả dự đoán được đánh giá và phân tích bằng cách sử dụng sai số bình phương trung bình (RMSE). Những kết quả này có thể cung cấp cơ sở và hướng mới để cải thiện quy trình thiết kế anten, đóng góp vào việc triển khai hệ thống không dây hiện đại và hiệu quả hơn. Kết quả dự đoán giúp giảm thời gian tối ưu hóa các tham số trong thiết kế anten.

Từ khóa:

Học máy trong anten, AI trong Anten, dự đoán thông số anten, anten patch.

1. INTRODUCTION

Machine Learning (ML) has seen significant growth in recent years with various applications such as image and speed recognition, recommendations, detection, virtual personal assistants, and specifically prediction. Prediction stands as a fundamental challenge in Machine Learning (ML), extracting valuable insights from data through robust prediction algorithms. In the domain of antenna design, ML is leveraged to optimize parameters and forecast antenna responses, enhancing efficiency and overall performance [1]. ML encompasses three primary types: supervised learning, unsupervised learning, and reinforcement learning, each employing distinct learning algorithms [2].

Supervised learning, a prevalent ML algorithm, forecasts new data outcomes based on known input-outcome pairs, proving highly effective across diverse inputs post-training on specific datasets [2, 3]. This category further branches into classification and regression. Conversely, unsupervised learning algorithms operate without assigning labels to input data, relying on inherent data organization for tasks such as clustering, anomaly detection, and neural networks. Reinforcement learning trains machines through reward and penalty mechanisms, enabling agents to sense, comprehend their surroundings, and learn via trial and error. This approach finds applications in resource management, recommendations, and robotics.

In the context of antenna design, ML, particularly supervised learning, has been extensively explored. Various antenna types, such as slotted microstrip patch, Yagi microstrip, ring compact microstrip, fractal, spiral, horn, monopole, and antenna arrays, have been designed using ML techniques [4]. These applications demonstrate the potential of ML to expedite the antenna design process, offering a substitute for traditional optimization approaches like genetic algorithms and simulated annealing. Despite the success, some publications utilize relatively small datasets, impacting model reliability. The challenge lies in predicting resonant frequencies based on input dimensions, showcasing the ongoing efforts to refine and expand ML applications in antenna design [5-15].

In this paper, a ML model is applied to design the patch antenna for different resonant frequencies. The input dataset of the model includes 1000 patch antenna size samples that are resonant at frequencies ranging from 0.8 GHz to 6 GHz. They are simulated by CST software and enriched via theoretical calculations of patch antennas. The training results of the model are used to predict the size of the antenna at the desired resonant frequency. By applying K-Nearest Neighbors algorithm is recommended for predicting patch antenna sizes with a root mean square error (RMSE) of 0.175. The prediction results obtained by the ML technique are similar to the simulated parameters obtained by CST.

2. ANTENNA DESIGN

A resonant patch antenna at any frequency is designed. The antenna consists of a radiation patch with a size of W × L, a feed line with a length of L_f on the FR4 substrate with a relative permittivity of 4.4 and thickness of 1.6 mm. The patch antenna structure is shown in Figure 1. The size of the radiator is calculated according to equations (1), (2), (3).

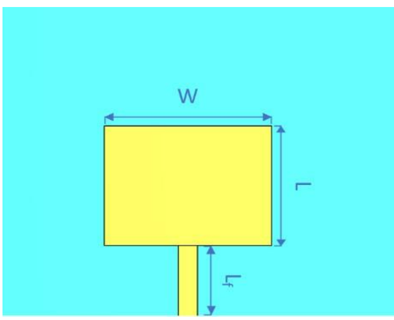

Figure 1. The structure of patch antenna at resosant frequency of 5.3 GHz

$$W = \frac{c}{2f_0\sqrt{\frac{\varepsilon_R+1}{2}}}; \quad (1)$$

$$\varepsilon_{eff} = \frac{\varepsilon_R+1}{2} + \frac{\varepsilon_R-1}{2}\left[\frac{1}{\sqrt{1+12\left(\frac{h}{W}\right)}}\right] \quad (2)$$

$$L = \frac{c}{2f_0\sqrt{\varepsilon_{eff}}} - 0.824h\left(\frac{(\varepsilon_{eff}+0.3)\left(\frac{W}{h}+0.264\right)}{(\varepsilon_{eff}-0.258)\left(\frac{W}{h}+0.8\right)}\right) \quad (3)$$

where f_0, ε_r and C denote resonant frequency, relative permittivity and velocity of light, respectively.

Effective dielectric constant (ε_{eff}) is calculated using equation (2), where h is thickness of the substrate.

Figure 2 depicts the return loss (S_{11}) of the antenna, respectively.

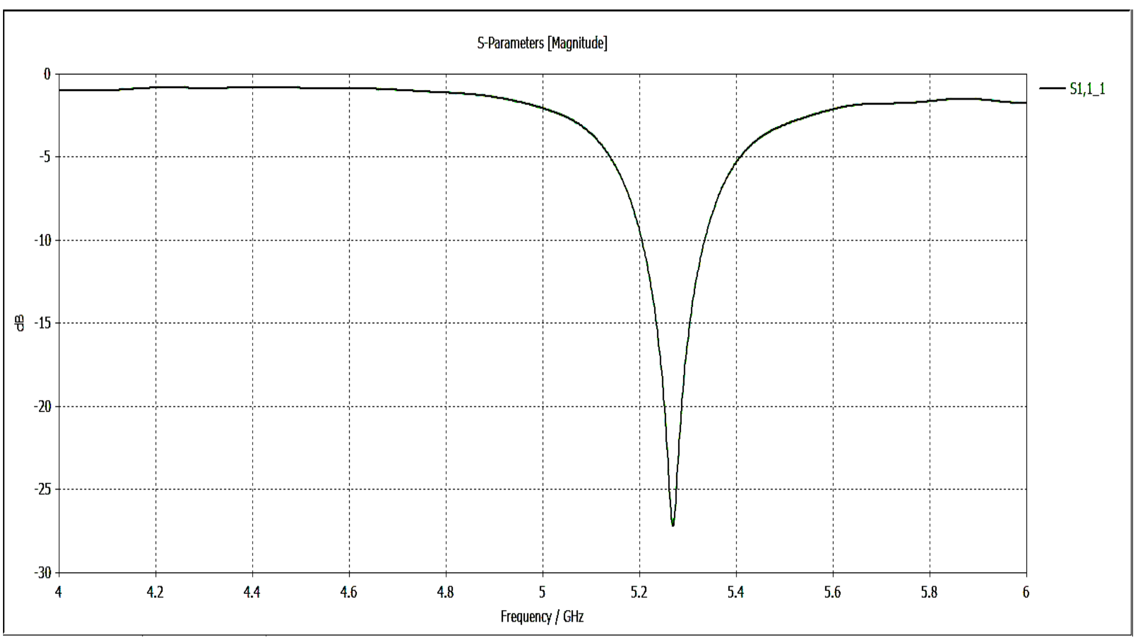

Figure 2. The simulated results of return loss

The initial radiator size is 26 mm× 20 mm and the feeder has a length of Lf =11.74 mm. The antenna operates at a center resonant frequency of 5.3 GHz with a bandwidth of 139 MHz.

3. APPLYING MACHINE LEARNING IN ANTENNA DESIGN

In antenna design, resonant frequency, bandwidth, gain and antenna efficiency are important parameters that affect antenna performance. In particular, the resonance frequency is an important parameter that needs to be designed and calculated right from the first step. In this article, based on the data set obtained during simulation on CST with patch antenna, we build a machine learning model to generate the corresponding dimensions from the input of the desired resonant frequency.

3.1. Dataset

We generated a dataset including parameters of resonant frequency, width and length of the patch, and length of the feeder. The width and length of the patch are calculated to operate at frequencies ranging from 800 MHz to 6 GHz. A total of 1000 records are used as input data for machine learning models. A record consists of four values separated by commas and stored as a csv file. This dataset can be easily used for different programming platforms, such as Python, Matlab, and C++.

The model's dataset is divided according to the following ratio: 80% of the dataset is used for training, 15% of the dataset is used for testing, and 5% of the dataset is used for validating the model and comparing.

The output of the model is a set of parameters used for Microstrip Patch Antenna design. The effectiveness of the proposed model is evaluated by the RMSE difference between the dataset performed with the model and simulated through CST software. The prediction errors are evaluated by RMSE (Root Mean Square Error) and it can depend on these algorithms as well as the condition and size of the data collected.

The machine learning model deployment process is depicted in Figure 3. Firstly, the RAW data from the CSV file is randomly shuffled, and then the dataset is divided into a ratio of 80/15/5 and fed into machine learning models to evaluate the results.

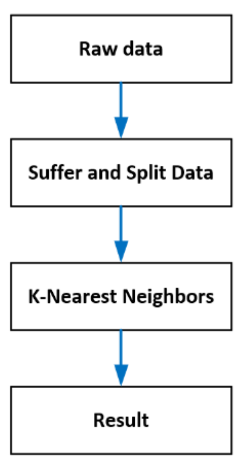

Figure 3. The performing process of ML model

3.2. Algorithm

The supervised regression algorithm discussed in this paper is the k-nearest neighbor (KNN) algorithm. Essentially, the KNN algorithm aims to predict new data points by identifying a specified number of training samples that are closest to the given point. This prediction is based on the concept of 'feature similarity', where the new point is assigned a value according to its resemblance to the training set. In the context of KNN regression, the input vector is denoted as x, the output vector as y, and k signifies the number of neighbors considered for prediction.

In this study, the parameters are selected based on the grid search method with the parameter n_neighbors in the range [1 - 100]. The parameter p, which is Power parameter for the Minkowski metric, ranges in [1 - 3]. The weight is selected between “uniform” and “distance”. The selection algorithm between “auto”, “ball_tree”, “kd_tree” and “brute”. The parameter set that gives the best results is n_neighbors = “5”, weight = “distance”, algorithm = “auto”, p = “1” to strike a balance between accuracy and computational efficiency, although alternative values are viable.

For the weighting mechanism employed here, a uniform weight is chosen. However, other options such as a weight of 1/d or alternative weights, where d represents the distance to the neighbor, can also be implemented. Furthermore, the Euclidean distance metric is utilized in this research to calculate distances. The neighbors are selected from the set of object values in the input data and act as the training set for the algorithm.

To deploy a KNN method, the following steps can be undertaken:

- Compute the distance between the new point and every training point.
- Select the k closest points based on the calculated distances.
- Utilize the weighted average value of these chosen data points as the ultimate prediction for the new point.

4. RESULT AND DISUSSION

Figure 4 depicts the results when applying ML model with KNN algorithm to the dataset. The figure shows the comparison between the actual and predicted values for antenna dimensions. The model is avaluated by RMSE (4) and R2 (5). The RMSE is Root Mean Square Error which is used to quantify the error between predicted value and actual value. The R2 is the Pearson correlation coefficient, which is used to quantify how well predicted value with actual value. The value of R2 is between 0 and 1, the closer R-squared is to 1 the better our model will predict our dependent variable.

$$\boldsymbol{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} \|y_i - \hat{y}_i\|^2}{N}} \qquad (4)$$

$$\boldsymbol{R_2} = \mathbf{1} - \frac{\sum_{i=1}^{N}(\boldsymbol{y_i} - \widehat{\boldsymbol{y}}_i)^2}{(\boldsymbol{y_i} - \overline{\boldsymbol{y}})^2} \tag{5}$$

Where, $\boldsymbol{y_i}$ are the values in the data set with N records, $\widehat{\boldsymbol{y}}_i$ are the model's predicted values, $\overline{\boldsymbol{y}}$ is the mean of the observed data.

The result analysis of algorithms KNN also shows that the RMSE is 0.07. The coefficient of determination (R2) reaches 0.9, which shows that the selected data set is completely suitable for this algorithm.

Table 1 shows examples of simulated dataset and predicted values of dimension for the KNN algorithm. It can be seen that the simulated values and the predicted values are similar. Several validation values are performed at the resonant frequencies of 0.8 GHz, 1.52 GHz, 2.50 GHz, 4.94 GHz, 5.87 GHz, and 6 GHz. Figure 5 shows several simulated and predicted S_{11} curves. It helps to easily observe the similarity between the simulation and prediction results.

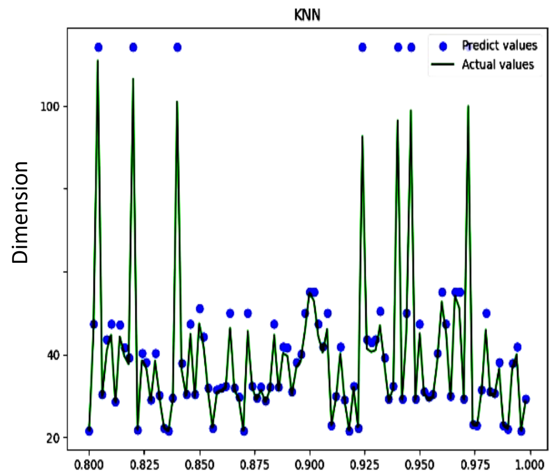

Figure 4. Comparison between actual and predicted value for antenna dimensions (W, L, L_f)

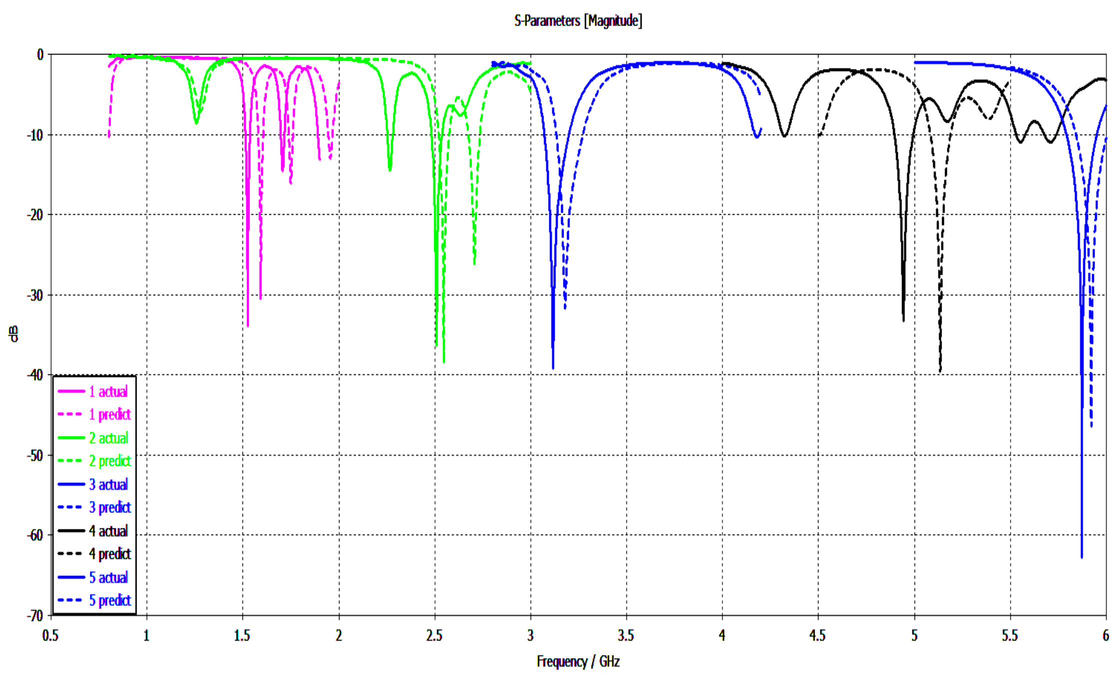

Figure 5. Comparison of simulated predicted S11 of patch antenna

Table 1. Examples of simulated dataset and predicted values of dimension for the KNN

No.	Frequency (GHz)	Simulated parameter (mm)			Predicted parameter (mm)		
		W	L	Lf	$\widehat{W}$	$\hat{L}$	$\widehat{L_f}$
1	0.8	114	89.16	51.37	112.2	88.52	51.10
2	1.52	81.66	92.34	51.11	80.23	90.07	50.34
3	2.50	61.66	55.77	35.18	51.06	55.12	20.07
4	4.94	53.66	41.75	24.18	51.42	40.10	21.15
…	…	…	…	…	…	…	…
999	5.87	23.14	17.12	9.86	22.S92	16.89	9.72
1000	6	15.20	11.32	3.80	14.01	9.87	3.66

5. DISCUSSION AND CONCLUSION

An ML model with KNN algorithm is applied to estimate the dimensions of the antenna at any desired operating frequency. The KNN algorithm is recommended for the patch antenna due to its low RMSE of 0.070. The comparison between simulation and prediction values has been performed with similarity. These findings may provide a foundation to enhance the process of antenna design. The prediction findings aid in minimizing the time required to improve parameters in antenna design.

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