# Design of Compact Patch Antenna Based on Support Vector Regression

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Submitted April 12, 2022 / Accepted July 11, 2022 / Online first August 3, 2022

**Abstract.** *In this paper, support vector regression (SVR) algorithm is used for compact patch antenna design. By etching three T-shaped slots on the ground plane of a rectangle patch antenna, the current distribution on the ground plane is changed and the resonant frequency is reduced. However, there is no reliable formula between the physical parameters of slots and the resonant frequency for antenna design. In this paper, the SVR algorithm is innovatively used to establish the mapping relationship between four parameters and the resonant frequency. In order to reduce the data samples required to train the SVR model, these four parameters are divided into three groups. This grouping method ensures the reasonable distribution of data samples, and greatly reduces the training data samples and reduces the time to collect data by simulator software. The hyperparameters are optimized by using 10-fold cross validation. 108 antenna models (data samples) with different geometrical and electrical parameters are designed and simulated for the initial dataset. The SVR model is trained on the 75 data samples with the coefficient of determination ($R^2$) of 0.9736 and is tested on the remainder 33 data samples. With the computation of the SVR model, the size of the proposed antenna decreases by 19.18% compared with that of the conventional rectangle patch antenna. The proposed structure is fabricated and measured. The results show that the proposed SVR model has good generalization on the real antenna model.*

## Keywords

Support Vector Regression (SVR), compact design, patch antenna, T-shaped slots

## 1. Introduction

Patch antennas are widely used because of their small size, easy integration and simple manufacturing process [1]. Rectangular microstrip antenna is one of the most basic patch antennas, and its patch shape has been developed into C-, E-, and L-shaped [2–4]. In order to further reduce the size of antennas, the method of etching slots on ground plane of antennas began to arise [5], [6]. However, the design of compact antenna is more trial and error than that of conventional antenna guided by closed formula. In the face of increasing difficulty and time consuming in antenna design, machine learning (ML) methods have been applied in antenna design to improve efficiency. After decades of development, both classical and improved machine learning algorithms have been fully applied in antenna design [7–14]. Deep neural network (DNN) is used to calculate the resonant frequency of the E-shaped patch antenna [15]. Lasso, artificial neural networks (ANNs) and K-nearest neighbor (KNN) is used to determine the optimal parameters of the double T-monopole antenna [16]. Under the premise of keeping the accuracy, the time spent by the machine learning methods in antenna design is less than that of the simulation software, which proves the feasibility of these methods in antenna design. A biggest advantage of these methods is that as long as a reliable machine learning model is established, the output values (predicted values) of all input parameters can be computed by the machine learning model, thus greatly improving the efficiency of antenna design. The support vector regression (SVR) algorithm is a method of support vector machine (SVM) algorithms specifically designed to solve regression problems. At present, SVR algorithm has been well applied in antenna impedance matching [17] and reflective array antenna design and optimization [18].

In this paper, the SVR algorithm is used to compute the resonant frequency of the proposed compact antennas. The input parameters of the SVR model include the relative dielectric constant of the substrate and the length of three T-shaped slots. A total of 108 antennas (108 data samples) are simulated through full-wave electromagnetic (EM) simulation. A number of 75 antennas (75 training samples) are used for the training and the remainder 33 antennas (33 testing samples) are used for testing the accuracy of the SVR model. The accuracy of the proposed SVR model is further tested on an antenna operating at 2.5125 GHz. The proposed SVR model is used to calculate the resonance frequency in the training samples and the test samples, and the statistical performance index accuracy of the determining coefficient ($R^2$) is 0.9736 and 0.9116, respectively. Through this SVR model, the time required to calculate the resonant frequency of antenna models is greatly reduced. The SVR model takes only 307 millisec-

DOI: 10.13164/re.2022.0339

onds to calculate at a time, while the HFSS simulation takes 30 seconds at a time. In the case of using an optimization algorithm, using the SVR model instead of the HFSS model can greatly reduce the optimization time. This lays the foundation for the use of optimization algorithms. The resonant frequency of the compact antenna is reduced from 3.18 GHz to 2.57 GHz by 19.18%, meanwhile the bandwidth is almost unchanged, which also verifies the effectiveness of the SVR algorithm in compact design.

## 2. Modelling

The process of establishing the SVR model is shown in Fig. 1, and the algorithm flowchart is shown in Fig. 3. The implementation of the method is demonstrated in the following steps.

*Step 1*: Determine the input parameters of the SVR model. The relative dielectric constant ($\varepsilon_r$) of the substrate and the length of three T-shaped slots ($L1$, $L2$, $L3$) are selected as the input parameters. The detailed structural parameters of the proposed antenna are listed in Tab. 1. and the structure is shown in Fig. 2.

*Step 2*: Initial data collection. 108 compact antenna samples with different physical sizes are designed. Then the initial dataset (108 samples) is generated through HFSS full-wave electromagnetic simulation for training and testing.

*Step 3*: Model training. 70% of the initial dataset, 75 data samples, is used as the training dataset. 30% of the initial dataset, 33 data samples, is used as the testing dataset. The SVR model is optimized on the training dataset by using 10-fold cross validation method. The coefficient of determination ($R^2$) is used as the evaluation index, and the calculation formula of $R^2$ is:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y})^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{1}$$

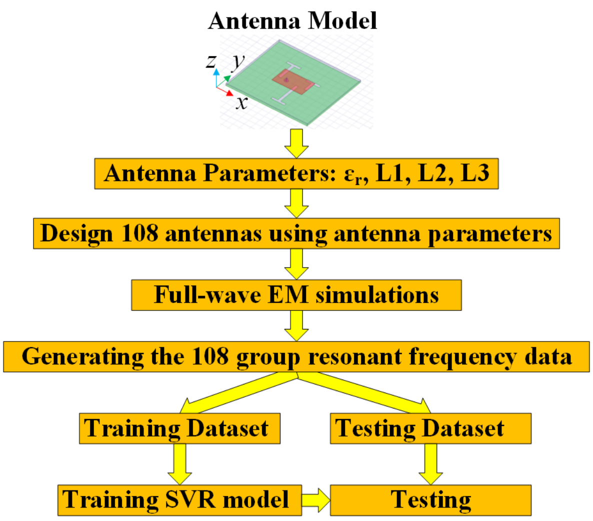



**Fig. 1.** Steps of antenna design based on SVR.

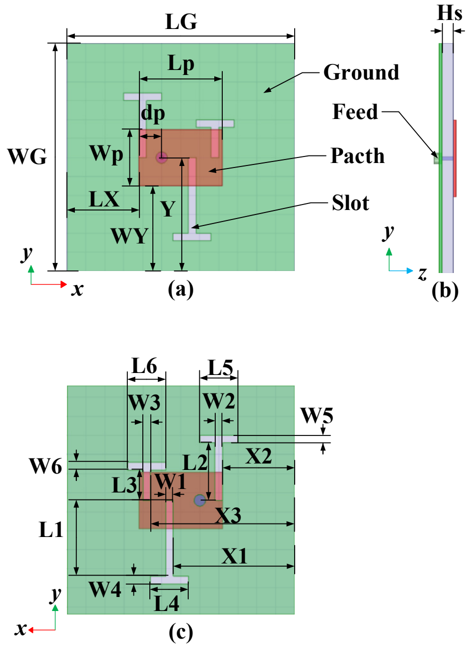



**Fig. 2.** Geometry of the compact antenna: (a) Top view, (b) side view, (c) bottom view.

| | | | | | | |
|---|---|---|---|---|---|---|
| Parameters | LG | WG | Hs | Lp | Wp | dp |
| Value | 60 | 60 | 1.6 | 22 | 15 | 5 |
| Parameters | LX | WY | Y | L1 | W1 | L4 |
| Value | 19 | 22.5 | 30 | 20 | 2 | 10 |
| Parameters | W4 | X1 | L2 | W2 | L5 | W5 |
| Value | 2 | 32 | 15 | 2 | 10 | 2 |
| Parameters | X2 | L3 | W3 | L6 | W6 | X3 |
| Value | 19 | 2 | 20 | 19 | 2 | 38 |

**Tab. 1.** Parameters of antenna (units: mm).

where $y_i$ is the real observed values, $\bar{y}$ is the average value of real observed values, $\hat{y}$ is the predicted value. A bigger $R^2$ means a better model. The closer $R^2$ is to 1, the more reliable the model is.

*Step 4*: Model validation. The reliability of the SVR model is verified on the testing dataset. If it is found that the SVR model trained in the previous step does not have good generalization on the testing dataset, it is necessary to re-train the model and adjust the model parameters, to ensure that the model has good fitting and good generalization on the testing dataset. In this step, linear regression model, random forest model and K-nearest neighbor model are established and compared with the SVR model to verify the advantages of SVR algorithm on this compact antenna.

### 2.1 Antenna Structure

A rectangular patch with $L_p \times W_p$ is printed on one side of substrate. Different from the rectangular microstrip antenna, three T-shaped slots are etched from the ground plane, which can effectively reduce the resonant frequency. The size of the three T-shaped slots on the ground plane can be equal or unequal. The substrate is FR-4 with $\varepsilon_r$ of 4.4, dielectric loss tangent angle of 0.02 and thickness of 1.6 mm.

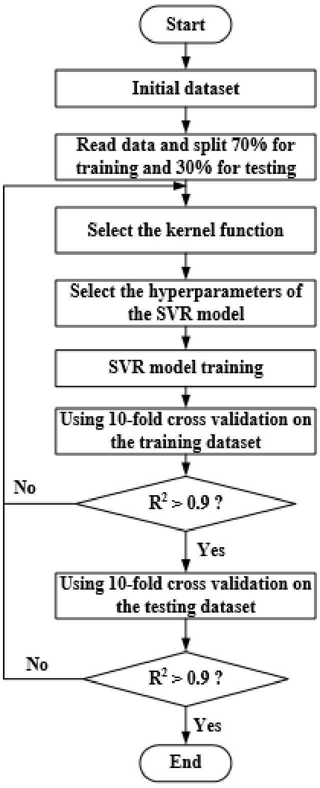



**Fig. 3.** Flowchart of training the SVR model.

Coaxial line or SMA connector can be applied to feed the proposed structure.

The performance of conventional rectangular patch antenna can be analyzed with cavity model theory, and the relevant design formula is:

$$\left(f_{\mathrm{r}}\right)_{mnp}=\frac{1}{2\pi\sqrt{\mu\varepsilon}}\sqrt{\left(\frac{m\pi}{h}\right)^{2}+\left(\frac{n\pi}{L}\right)^{2}+\left(\frac{p\pi}{W}\right)^{2}} \tag{2}$$

where $\varepsilon$, $\mu$, $h$ are the dielectric constant, permeability and thickness of the substrate, respectively, $L$ is the length of the patch, $W$ is the width of the patch, $m$, $n$, $p$ is, respectively, the number of half-cycle field variations along the $x$, $y$, $z$ directions.

The antenna mainly works in $TM_{010}$ mode, so its resonant frequency is:

$$\left(f_{\mathrm{r}}\right)_{010}=\frac{1}{2L\sqrt{\mu\varepsilon}}=\frac{\upsilon_0}{2L\sqrt{\varepsilon_{\mathrm{r}}}} \tag{3}$$

where $v_0$ is the velocity of light in free space, $\varepsilon_r$ is the relative dielectric constant of the substrate.

According to (3), the resonant frequency of the antenna is mainly determined by the patch size and the relative dielectric constant $\varepsilon_r$ of the substrate, and without the ground plane. In fact, $L$ in (3) can be understood as the effective length of the current. The design of etching slots in the ground plane increases the effective length of the current, thereby reducing the resonant frequency of the antenna, thus achieving the purpose of compact design.

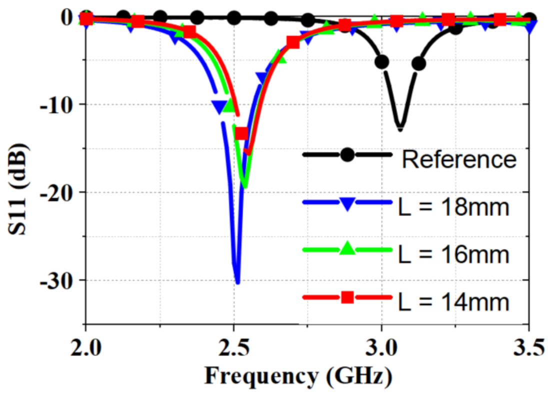
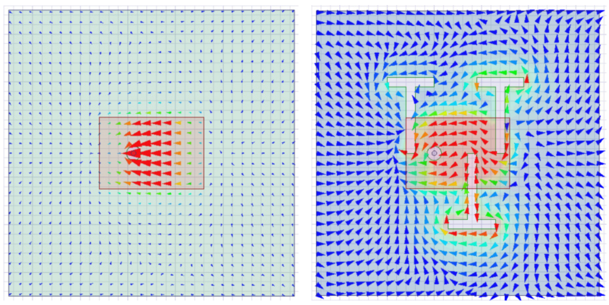



**Fig. 4.** The return loss curves (S11) of antennas with the same geometry, only the parameter $L$ changes.

However, there are no corresponding formulas for the design of slots. The design can only be verified by trial and error. Now, the SVR model trained in this paper solves this problem and establishes the correspondence between the shape of slots and the resonant frequency. Through this SVR model, the resonant frequency can be obtained quickly.

In order to reduce the resonant frequency, three T-shaped slots are etched from ground plane of the rectangular patch antenna. To verify the effect, the length of three slots is initially set to the same variable, namely parameter $L = L1 = L2 = L3$. After parametric analysis of $L$, the return loss (S11) is shown in Fig. 4, from which, it can be noticed that the resonant frequency of the conventional rectangular antenna (reference antenna) is 3.0625 GHz. As the length of the slots is increased, the resonant frequency is decreased. Figure 5 shows the current distribution on the ground plane with and without slots. It can be seen that the current is concentrated under the patch and flows to the feed point when the ground is intact. When three T-shaped slots are etched, the current flows along the edge of the slots. In other words, the effective length of the current increases. The increase of current path can be applied to reduce the resonant frequency.

However, there is no specific formula to describe the effect of slot's size on resonant frequency. By means of the full-wave electromagnetic simulation software, the corresponding relationship between the length of each slot and resonant frequency can be sought, which is very unfavorable



(a) (b)

**Fig. 5.** Current distribution. (a) Patch antenna. (b) Patch antenna with T-shape slots.

to the design and application of antenna. Therefore, the SVR algorithm is used to establish the prediction model of the resonant frequency. This prediction model can quickly calculate the resonant frequency without the need for the full-wave simulation, which is convenient for antenna compact design and application.

## 2.2 Data Collection

With the analysis of mechanism of the proposed compact antenna, it is found that the $\varepsilon_r$ of the substrate and the length of the T-shaped slots have essential effects on the resonant frequency. Therefore, four parameters ($\varepsilon_r$, $L1$, $L2$, $L3$) are selected as the input parameters of the SVR model. The output value is the resonant frequency of the compact antenna. In order to reduce the amount of data collected, these four parameters are divided into three groups, and a total of 108 antennas are designed, 36 in each group, as shown in Fig. 6. We set the range for each parameter first, where $\varepsilon_r$: 4–4.8, $L1$: 6–22, $L2$: 6–22, $L3$: 7–22.

Since the length of T-shaped slots has an obvious influence on the resonant frequency, 9 samples of $L1$ are selected. $L2$ and $L3$ have a certain symmetry relationship for the feed points, and their influences are relatively consistent. Therefore, 6 samples are selected respectively. Finally, 108 data samples are generated through HFSS full-wave electromagnetic (EM) simulation. Figure 7 shows the resonant frequency distribution of 108 antennas. The physical parameters of antenna numbered 1 are $\varepsilon_r = 4.0$, $L1 = 6$ mm, $L2 = 6$ mm, and $L3 = 7$ mm, other physical dimensions are shown in Tab. 1, and so on. It can be seen from the figure that the calculation results of three groups of data have similar distribution rules. Meanwhile, all resonant frequencies vary from 2.3000 to 2.9750 GHz. After data collection is completed, testing dataset and training dataset are divided. The SVR model is trained on the training dataset.

## 2.3 Training

The SVR algorithm is sensitive to the selection of kernel function, which directly determines the final performance of the SVR algorithm. The SVR algorithm with different kernel functions has different hyperparameters, also. Therefore, four common kernel functions including linear kernel function, polynomial kernel function, Gaussian kernel function and sigmoid kernel function are selected to train the nonlinear SVR model, and the grid search method is used to find the optimal hyperparameter values. The model evaluation method is 10-fold cross validation, and the evaluation index is $R^2$. The performance of SVR models with different kernels on the training dataset and testing dataset is shown in Tab. 2. When the linear kernel function is used, the $R^2$ on the training dataset is 0.7516, while when the polynomial kernel function is used the $R^2$ on the training dataset is 0.8597, indicating that there is a nonlinear relationship between the structural parameters of the antenna and the resonant frequency. When Gaussian kernel function is used, $R^2$ on the training dataset reaches 0.9736. It can be seen that Gaussian kernel function is more suitable for this dataset.

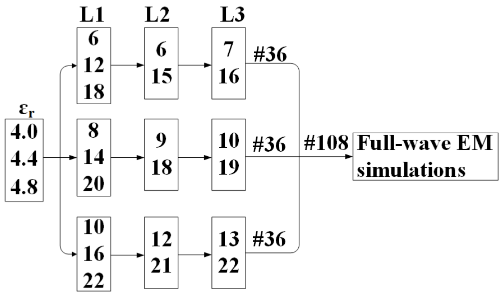



**Fig. 6.** Topological illustration of the geometrical and electrical parameters of the simulated 108 antennas (dimension unit: mm).

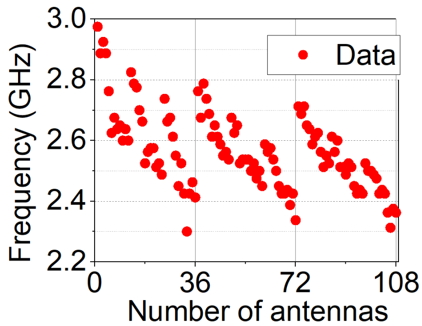



**Fig. 7.** Simulated resonant frequency for each antenna defined in Fig. 5.

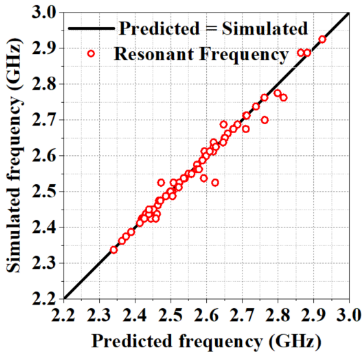
| Kernel functions | $R^2$ (train datasets) | $R^2$ (test datasets) |
|---|---|---|
| Linear kernel function | 0.7516 | 0.8193 |
| Polynomial kernel function | 0.8597 | 0.7422 |
| Gaussian kernel function | 0.9736 | 0.9166 |
| Sigmoid kernel function | 0.1996 | 0.1171 |

**Tab. 2.** Different kernel functions perform on the dataset.

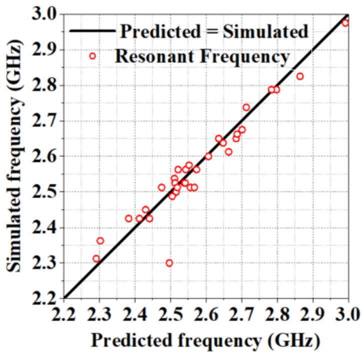
## 2.4 Testing

The model is verified on the testing dataset after training. The performance of the model on the training dataset is shown in Fig. 8(a), with $R^2$ of 0.9736, and that on the testing dataset is shown in Fig. 8(b), with $R^2$ of 0.9116. It can be seen that the SVR model has good fit on the training dataset and good generalization on the testing dataset, proving that the regression model is completely reliable. When $\varepsilon_r$=4.4, $L1$ = 20 mm, $L2$ = 15 mm, $L3$ = 8 mm, the result of the calculation of the SVR model is 2.5125 GHz, and the result of simulation of HFSS is 2.5700 GHz, with a relative error of 2.24%.

Table 3 lists the performance of SVR model, linear regression model, random forest regression model, K-near-




(a)




(b)

**Fig. 8.** Scatter diagrams of the simulated and predicted resonant frequency (unit: GHz) values by the SVR model: (a) Training dataset, (b) testing dataset.

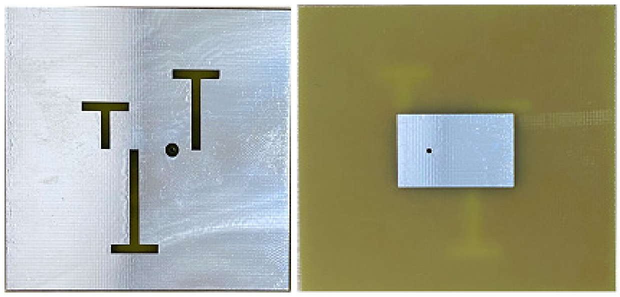
| Method | $R^2$ (train datasets) | $R^2$ (test datasets) |
|---|---|---|
| Support vector regression | 0.9736 | 0.9116 |
| Linear regression | 0.8591 | 0.8171 |
| Random forest regression | 0.8745 | 0.7921 |
| K-nearest neighbor | 0.1751 | 0.0961 |
| Gaussian regression | 0.9999 | 0.0132 |

**Tab. 3.** Different machine learning models perform on the initial dataset.

est neighbor model, and Gaussian regression model on this initial dataset. It can be seen from the table that when linear regression is adopted, $R^2$ on the training dataset and testing dataset is 0.8591 and 0.8171 respectively, which further indicates that the relationship between antenna structural parameters and resonant frequency is not completely linear. When Gaussian regression algorithm is adopted, the established model performs very well on the training dataset, with $R^2$ reaching 0.9999. However, it performs very poorly on the testing dataset, with only 0.0132, indicating the inapplicability of Gauss regression algorithm on this data dataset. Compared with other algorithms, the proposed SVR model has good performance in both training dataset and testing dataset.

# 3. Experimental Results

In order to further verify the correctness of the SVR algorithm, the proposed compact antennas are simulated by full-wave electromagnetic solver, calculated by SVR algorithm, and fabricated and measured. The photographs of the fabricated prototype are shown in Fig. 9. Three T-shaped slots with different lengths are etched out from the ground plane, which is shown in Fig. 9(a).



(a) (b)

**Fig. 9.** Photograph of the fabricated antenna: (a) Back view, (b) top view.

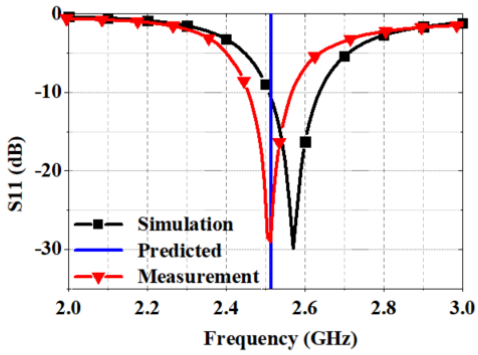
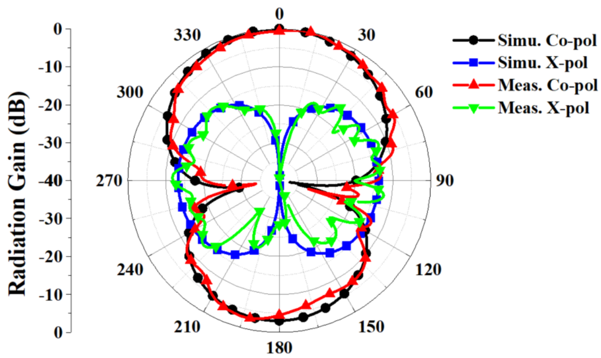
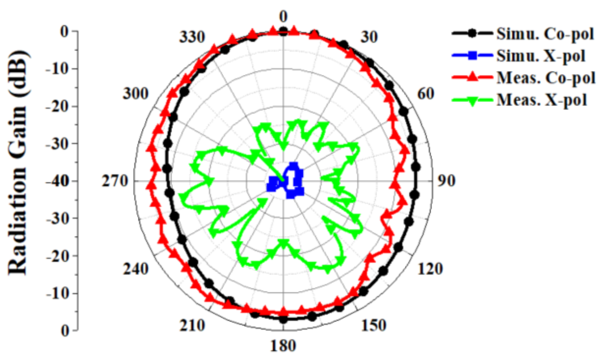



**Fig. 10.** The return loss curves (S11) of the fabricated antenna.




(a)




(b)

**Fig. 11.** 2D radiation patterns of the fabricated antenna: (a) XOZ-plane, (b) YOZ-plane.

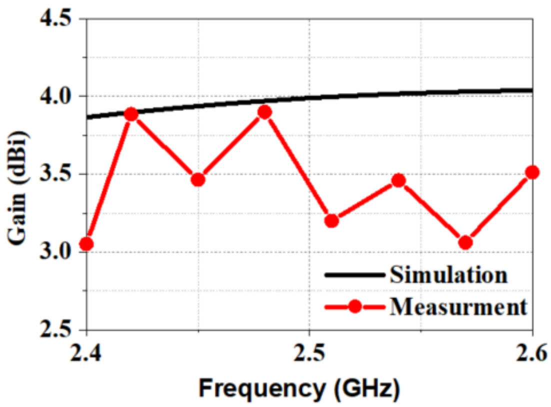



**Fig. 12.** Gain curves of the proposed antenna.

The scattering parameter of antenna is measured with vector network analyzer AV3656A. The predicted data, simulated data and measured data are presented in Fig. 10. There, it can be noticed that the simulated resonant frequency is 2.5700 GHz, while the measured frequency is 2.5124 GHz. There is only a very small relative error of 2.24%. The radiation patterns of the fabricated antenna are tested using a far-field antenna test system. The XOZ- and YOZ-plane radiation patterns are shown in Fig. 11(a) and (b), respectively. As can be seen from the figure, the antenna mainly radiates energy towards +Z axis, and the energy in x-axis direction is 0. At the same time, the antenna has a cross polarization level of more than 20 dB in the 0° direction. The agreement between simulated and measured data is very good. The gain curves of the antenna near the resonant frequency are depicted in Fig. 12. It can be seen that there is a maximum error of 0.8 dB between simulated and measured data, which is mainly due to the loss of SMA connector, cable and test error.

## 4. Conclusion

The design of compact antenna with the help of SVR algorithm is proposed in this paper. Based on the traditional rectangular patch antenna, three T-shaped slots are etched out from ground plane for reducing the resonant frequency. Then, SVR algorithm is introduced to study the influence of T-shaped slots on the resonant frequency. The model is trained on a training dataset with only 75 training data samples and tested on a testing dataset with 33 data samples. The $R^2$ of the SVR model on the training dataset and testing dataset are 0.9736 and 0.9116, respectively. Several other regression models are trained with the same dataset for comparison. The proposed structure is computed, validated by a full-wave EM simulation and measured. The results show that the proposed compact antenna has a stable radiation and a gain error of less than 0.8 dB, while its resonant frequency is 2.5700 GHz with a decrease of 19.18%. The SVR model takes only 307 milliseconds to calculate at a time, while the HFSS simulation takes 30 seconds at a time. Therefore, the SVR algorithm has proved to be effective and practical in the design of compact antennas.

## Acknowledgments

This work is supported partly by the Natural Science Foundation of Zhejiang Province under contract of LGG21F010007, partly by “pioneer” and “Leading Goose” R&D program of Zhejiang under contract of 2022C01119, partly by the National Natural Science Foundation of China under Contract of 62171169.

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