Mansoura Engineering Journal

Volume 48 | Issue 3 Article 4

2023

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Shoeab, Hadeer. A; A.Mohamed, Mohamed; El Said A, Marzouk; and Kabeel, Ahmed. A. (2023) "Microstrip Antenna Design Using CST Optimized By Neural Network Algorithm," *Mansoura Engineering Journal*: Vol. 48 : Iss. 3 , Article 4.
Available at: https://doi.org/10.58491/2735-4202.3045

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ORIGINAL STUDY

Microstrip Antenna Design Using CST Optimized by Neural Network Algorithm

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Abstract

In this paper, a general design procedure is suggested for the microstrip antennas using artificial neural networks and this is demonstrated using the rectangular patch geometry. The model was analyzed for 1733 data sets of input output parameters. 1300 samples for training and 433 samples for testing and 1500 epoch, learning rate from (0.003−0.005). Python was used to create and implement the ANN algorithm model. The mean error in detection of resonance frequencies (return loss peaks) was 0.144 GHz on train set, and 0.116 GHz on test set. The outputs of the radial basis function are optimized by varying the number of neurons and hidden layers. The proposed method's results are compared with the results of CST and found to be in good agreement.

Keywords: Artificial neural network, Computer simulation technology, Microstrip patch antenna, Radial basic function, Return loss

1. Introduction

The design of high performance Low profile antennas may be necessary in applications for high-performance satellites, aircraft, airships, missiles, and spacecraft where size, weight, cost, performance, ease of installation, and aerodynamic profiles are limitations. Currently, microstrip antennas are used in a variety of government and commercial applications, including wireless, radio, and mobile communications (Thakare and Singhal, 2010; Kushwah and Tomar, 2009; Krishnan et al., 2007; Güneş et al., 2006; Srivastava et al., 2018) Different algorithms and techniques play an important part in this quickly growing and constantly changing period of science and technology. Many research concentrate on the development of wireless communication systems for the wireless systems by the design of such systems. The development of low-cost, high-bandwidth antenna technologies recently has improved the overall effectiveness and performance of the entire wireless system. Antennas can be designed using a variety of techniques to function at the desired resonant frequency. To improve the electrical performance parameters and the operation of antenna systems, however, theoretical and experimental studies are conducted. Researchers from several fields worked to create various antenna models. Choosing the settings for a specific resonance frequency for a given application is a difficult task. The various mechanical characteristics of the antenna system will depend more heavily on the operating frequency or resonant frequency. However, a scientific approach or an algorithm must be used to carry out the substantial analysis required for the computation of the mechanical parameters that define the frequency of operation (Kantipudi et al., 2021).

Several Machine Learning approaches have been used to learn the mapping between mechanical characteristics of antennas and their operation frequency. This technique has significantly

Received 11 January 2023; revised 25 April 2023; accepted 25 April 2023.
Available online 1 July 2023

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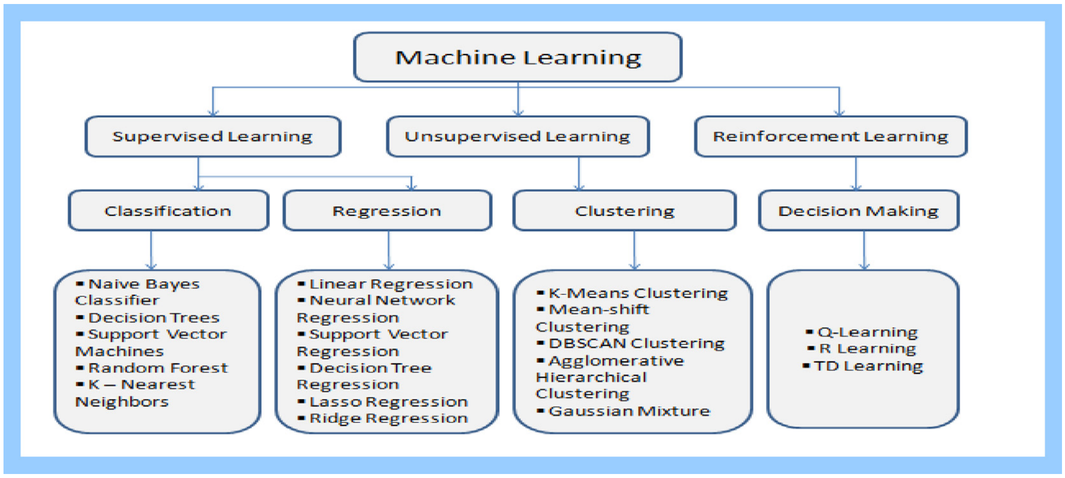

Fig. 1. Types of machine learning with examples.

changed how simple it is to construct antennas for different frequencies (Krishnan et al., 2007). The types of ML used are listed below dependent on the data provided for each problem that needs to be taught in order to detect patterns and predict better outcomes. Different applications have used these kinds of learning (Fig. 1) lists a limited number of uses: (Chinnasamy, Devarajan).

(1) supervised learning
(2) Unsupervised learning
(3) Reinforcement learning

2. Antenna design analysis

2.1. Rectangular microstrip antennas

The rectangular microstrip antennas are made of a rectangular patch with dimensions (the width of patch Wp &the length of patch Lp), the width of ground &substrate Wg, the length of ground &substrate Lg and the feeding point x&y which make matching of Z impedance = 50 ohm (Fig. 2).

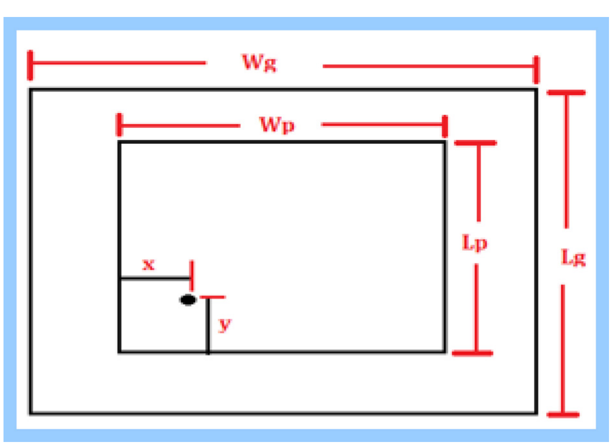

Fig. 2. Microstrip patch antenna structure.

2.2. Dataset description

The dataset consists of the response of 1733 antennas with different configurations of dimensions (Wp, Wg, Lp, Lg) and the position of feeding point (x, y) (Table 1). For each configuration of dimensions, antenna response represented by the return loss S11 over the frequency range [3–12 GHz] was obtained using CST. We define the resonance frequency of each antenna as the frequency with lowest return loss.

The ratio Lg/Wg varies between 0.4 and 11 for the simulated antennas. As the figure shows, most of represented points form lines perpendicular to the axes, since they were set by fixing 5 antenna parameters and changing the lasting parameter gradually (Fig. 3).

As shown in (Fig. 4) resonance frequencies spread over the range [3–12 GHz]. In addition, the return loss at resonance frequency varies between −10 and −70 dB. Some of points in the figure are arranged in vertical lines, they reflect the fact that changing a single antenna parameter may not affect its resonance frequency but rather it changes the return loss.

Here are the full response of 4 special antennas in the data set: the two antennas with highest and lowest resonance frequencies, and the two with largest and smallest return loss at the resonance point (Fig. 5).

2.3. Data preprocessing – train/Val/test split

(1) The dataset consists of the return loss response of 1733 different antennas, each one consists of 1001 samples of the operation frequency, and then the whole data table has 1,734,733 entries. These responses were divided into a training set

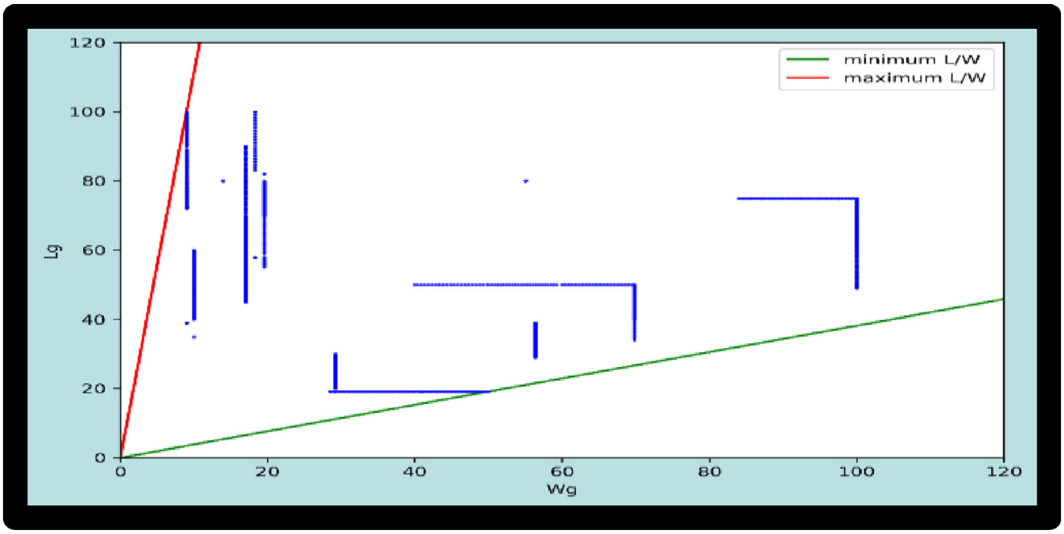

Fig. 3. Relationship between outer dimensions (Wg, Lg).

Table 1. The dimensions of antenna design.

	Wg	Wp	x	y	Lg	Lp
min	9	7	0	0	19.1	9
max	100	83	7	3.55	100	85

of 1300 antenna responses and a testing set of the remaining 433. This set was used to get objective analysis of the final performance of the model. When training neural network models, a validation set was randomly select from the training set at every training epoch with a ratio of 10% of the set = (130 response). This set was used to provide a metric of the model ability of generalization over unseen data during the training process.

The choice of RBF because this model of optimization fits the output S11 with a sum of RBF functions with trainable parameters. This idea was inspired by observing the curves of multiple antenna responses. They can be decomposed to a sum of bell-shaped function with different centers, widths, and amplitudes.

2.4. Structures and analysis of the neural network algorithm for microstrip patch antenna

In This section examines how dealing with high-dimensional data makes it exponentially harder to generalize to new cases and how typical machine learning's techniques for generalization are unable

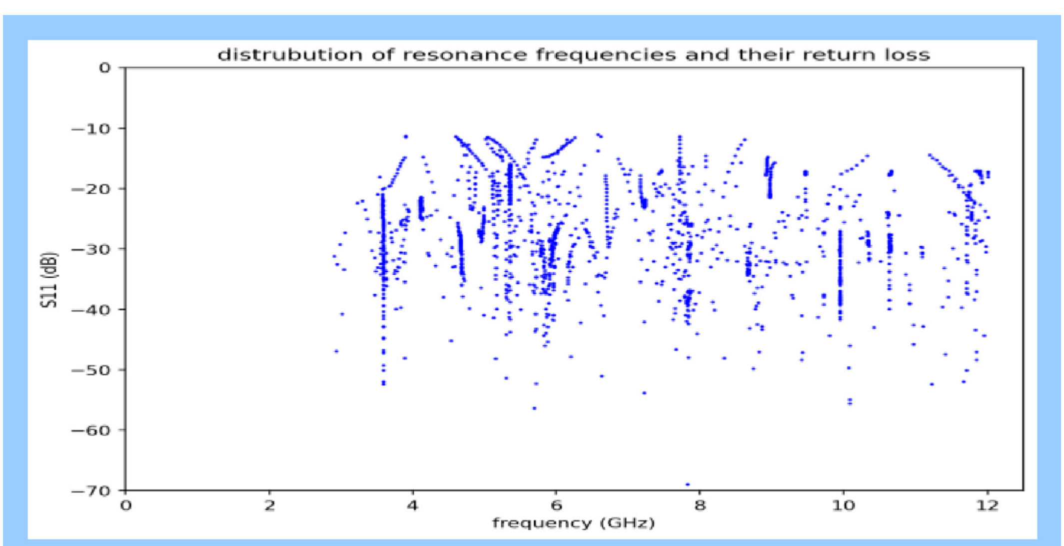

Fig. 4. The distribution of resonance frequencies of simulated antennas.

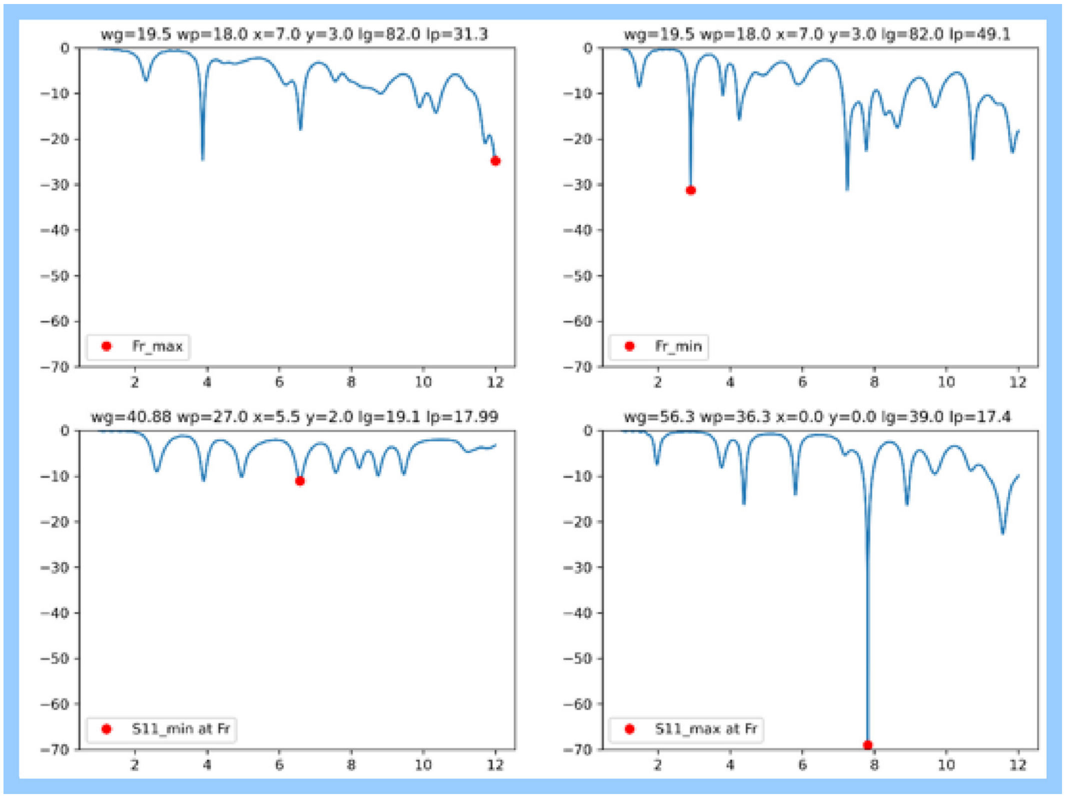

Fig. 5. Return loss for different samples.

to learn complex functions in high-dimensional environments. These areas frequently have substantial computational expenses. Deep learning was created to get around these problems as well as others (courville ian goodfellow, 2016).

A neural network model for RMSA (rectangular microstrip antenna) is used, and it uses the feed forward standard back propagation algorithm. This is a supervised neural network model for RMSA is shown in Fig. 6 and dimension is shown in Table 1. The supervised network model is trained using input data and target (output) data. The weights of the network are computed by training the network using the back propagation algorithm.

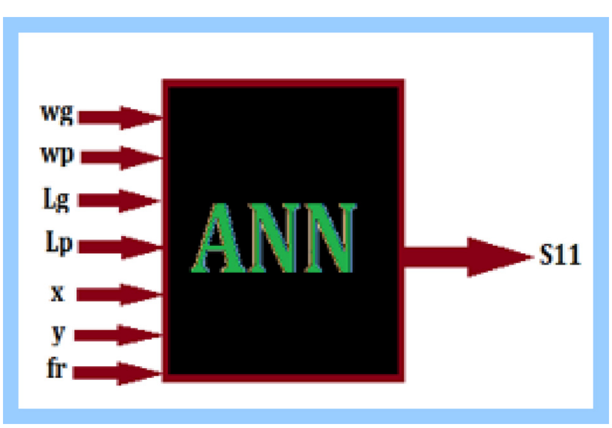

Fig. 6. The analysis ANN model.

2.5. First fitting approach (predicting fr): Fig. 7

(1) Several traditional ML methods were used to learn the mapping between antenna mechanical parameters and the resonance frequency. In the following section, we present these models and their performance:

2.5.1. Tested ML models other than neural networks

(1) K-Nearest Neighbors regressor: It can be noticed that the best test accuracy was achieve when K = 2 with a mean square error of approximately 0.75 (Fig. 9)
(2) Linear Regression with generated polynomial features: The figure shows that the best performance was at a polynomial of degree 5 (Fig. 10)
(3) Random Forest Regressor: For a fixed number of 100 trees, The test mean squared error settles at 0.75 after a maximum depth of 12 (Fig. 11)

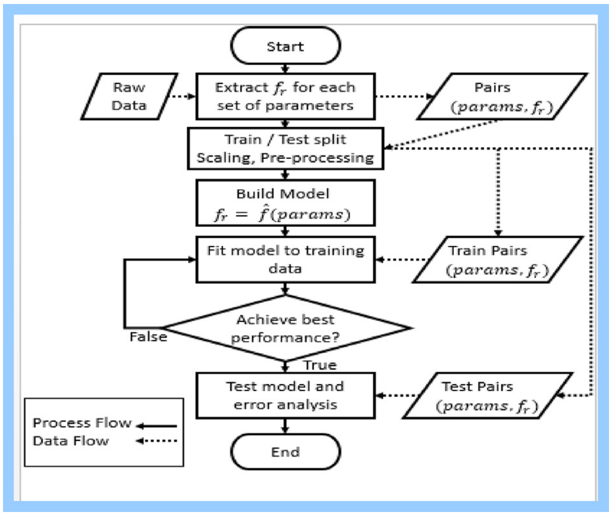

Fig. 7. Flow chart of building the first model (predict fr directly using antenna parameters only).

(4) Linear Regression with L2 Regularization: The figure demonstrates how a value of $\alpha = 10^{-2}$ gives the best test error (Fig. 12)

2.6. Second fitting approach (predicting S11): Fig. 8

Since the approach based on *fr* prediction using antenna parameters is too noisy and non-representative, another approach was proposed. The new model tries to predict the full frequency response of each antenna. In other words, the regression model estimates the value of return loss S11 at every frequency based on physical parameters of the antenna. This model fits the output S11 with a sum of RBF functions with trainable parameters. This idea was inspired by observing the curves of multiple antenna responses. They can be decomposed to a sum of bell-shaped function with different centers, widths, and amplitudes.

(1) The first fitting approach as well, we trained a multi-layer perceptron (MLP) to perform this fitting. For this type of model, there are a wide range of hyperparameters to tune. We conducted a randomized search to determine the best structure of MLP. This list summarizes the parameters considered in the tuning process.
  (a) The number of hidden layers, which varies between 1 and 12.
  (b) The number of neurons in each hidden layer, which varies between 5 and 85.
  (c) The activation function of the hidden layers. The tested functions were the Rectified Linear Unit (ReLU) and the hyperbolic tangent.
  (d) The learning rate, this hyperparameter controls the speed of the learning process,

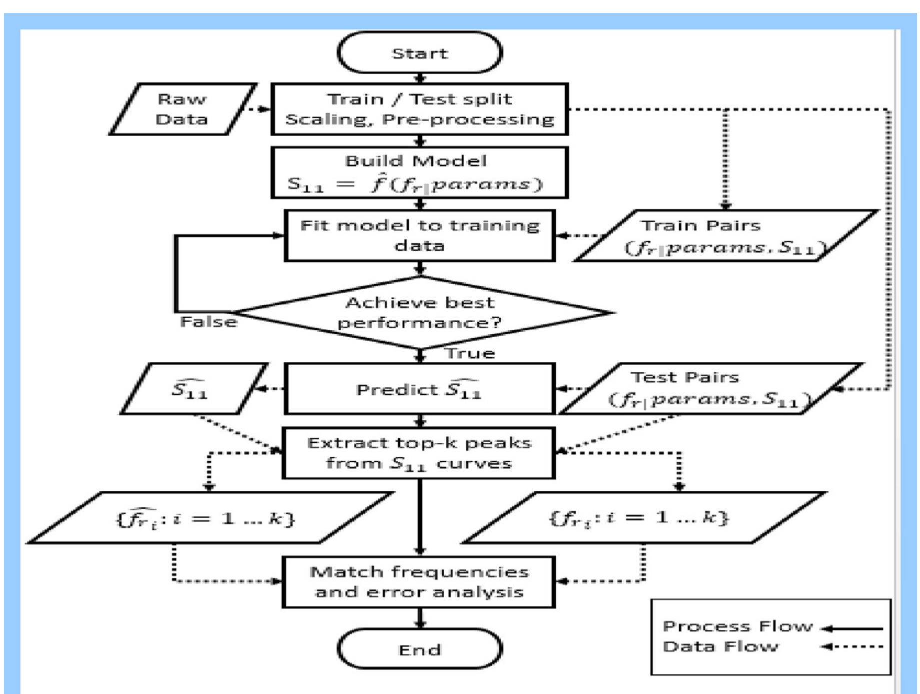

Fig. 8. Flow chart of building the second model (predict full S11curve then extract peaks as resonance frequencies).

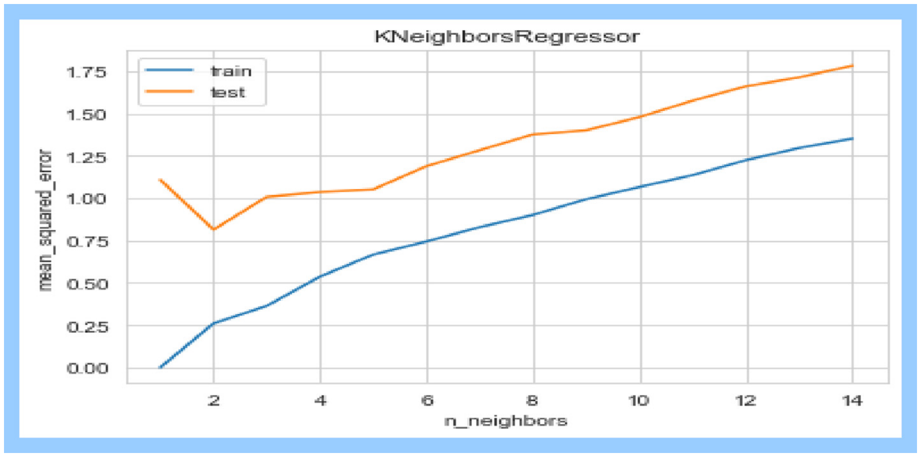

Fig. 9. K-Nearest Neighbors regressor.

the experimented values was exponentially distributed (3e-4, 1e-3, 3e-3, and 1e-2).

This is a diagram of a model that has 3 hidden layers with 40 neurons for each, and the activation function is ReLU (Fig. 13).

RFB unit illustration (Fig. 14):

$$f(x) = Ae^{-\left(\frac{x-C}{D}\right)^2} \quad (1)$$

2.6.1. RBF network

As mentioned before, the usage of RBFs was motivated by the general shape of response curves. The proposed model consists of 200 trainable RBF units. The general formula of the approximation function is (Fig. 15)

$$\widehat{S_{11}}\,(f) = \sum_{i=1}^{N} a_i e^{-\left(d_i\left(f-c_i\right)\right)^2} + b \text{ as shown in Fig. 15} \quad (2)$$

Where c_i, d_i are coefficients that depends on antenna parameters, they are computed by two separated linear layers. The coefficients a_i are the weight of the output layer and b is the overall bias (learned by the output layer).

The following diagram demonstrates the structure of the proposed model.

2.7. Training process

(1) The learning rate, which is a hyperparameter that control learning speed, was set to 3×10^{-3} at the beginning of training. This value was set after some experiments on different hyper-parameters values and that value achieve the better performance. The process of training consist of 1500 epochs. At each epoch, the data

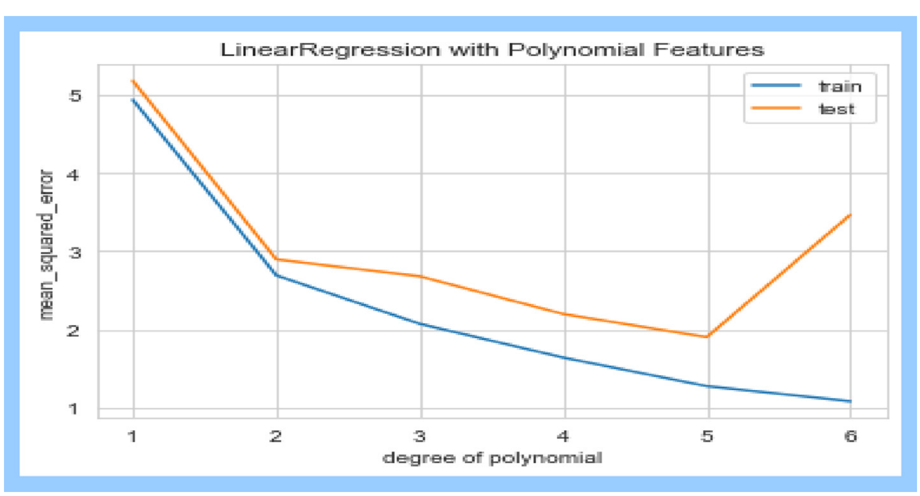

Fig. 10. Linear Regression with generated polynomial.

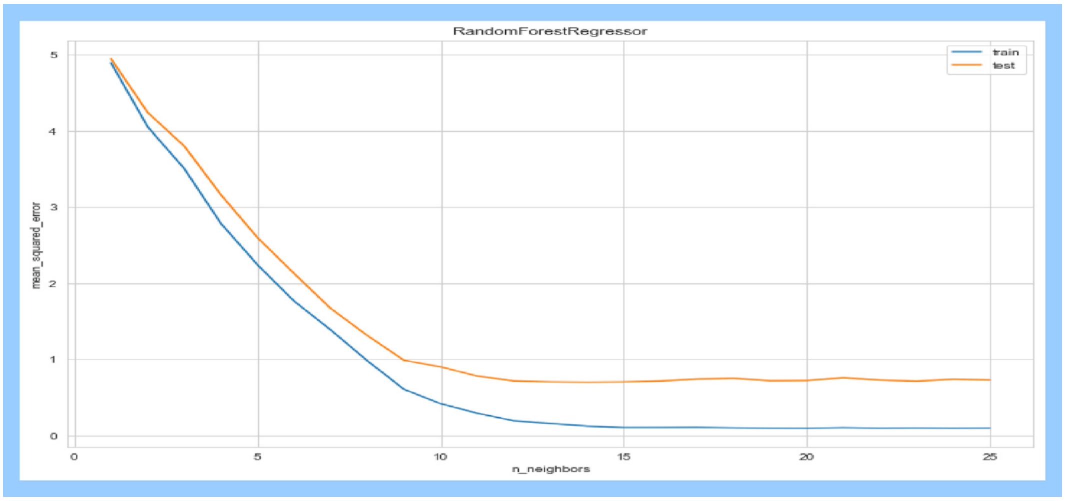

Fig. 11. Random forest regressor.

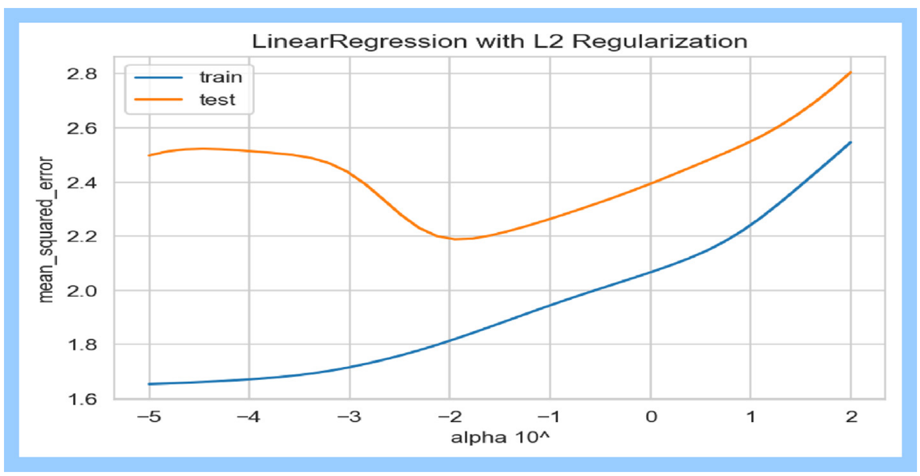

Fig. 12. Linear regression with L2 regularization.

was feed to the model batch by batch. The size of each batch is 1001 entries, the same as the size of one antenna response. However, evaluation loss reached a steady value after approximately 800 epochs, so training can be terminated at an earlier point. This practice achieved better convergence, one possible explanation for this is that the model tries to optimize its weights for a specific antenna at each step, not for a group of different antennas. However this practice increase the training time, because it make computations more sequential than parallel. Another technique applied during training is the learning rate decay. It is a function that is called at the end of every epoch to reduce the learning rate exponentially, so that after 1500 epochs it will be divided by 50. This technique helps to reduce oscillations loss function when the model get close to the optimal state of coefficients. Cross-

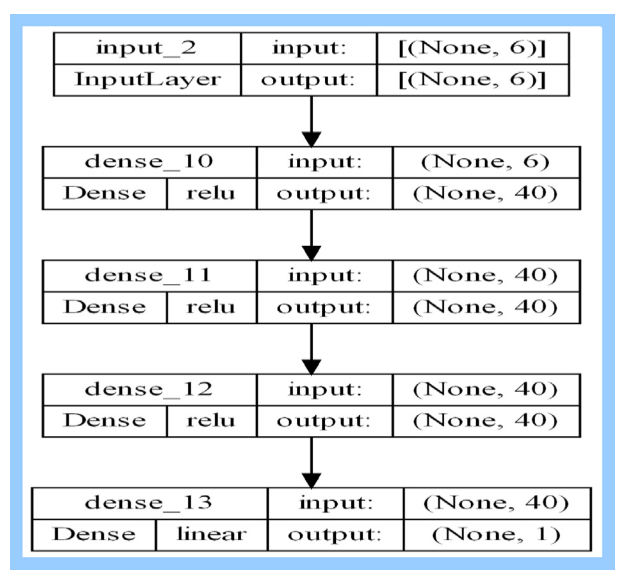

Fig. 13. The structure of the trained ANN.

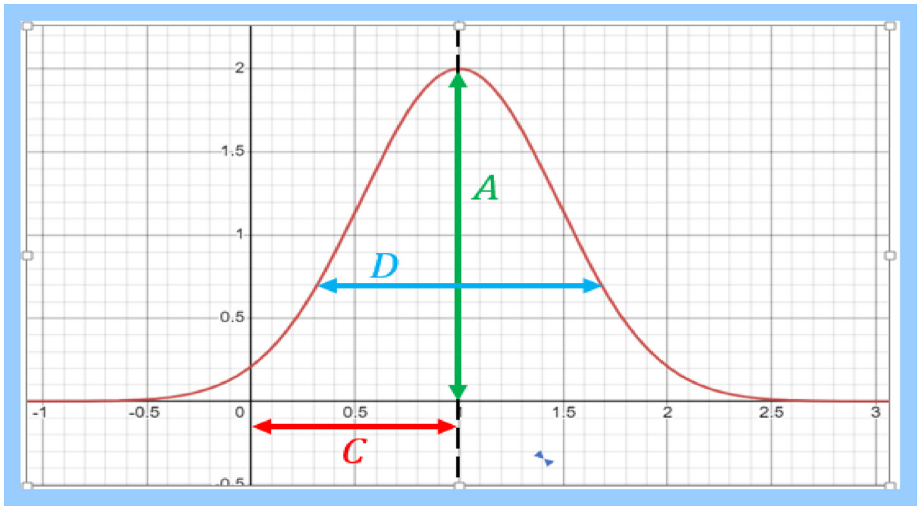

Fig. 14. Parameter of f(x) as A, C&D.

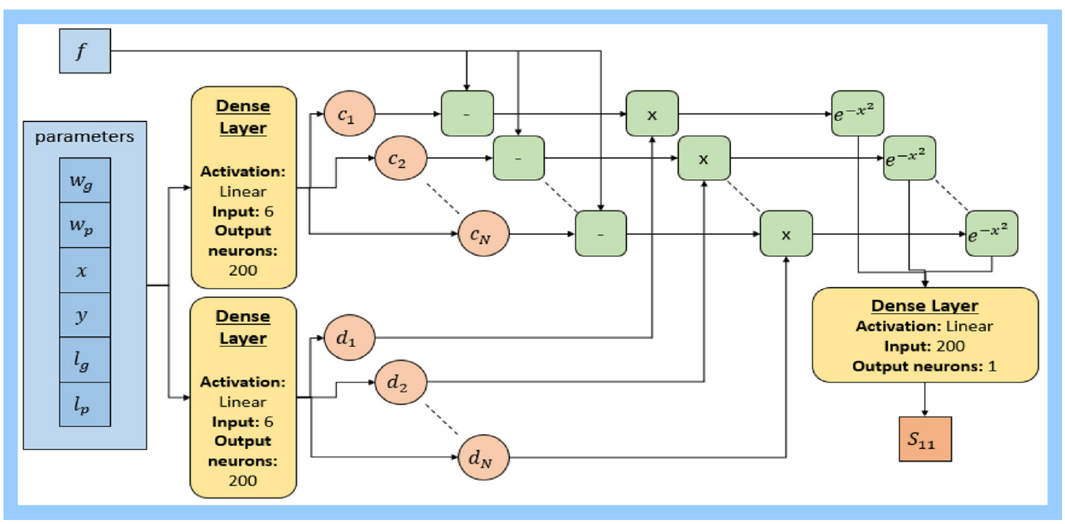

Fig. 15. The structure of the proposed model.

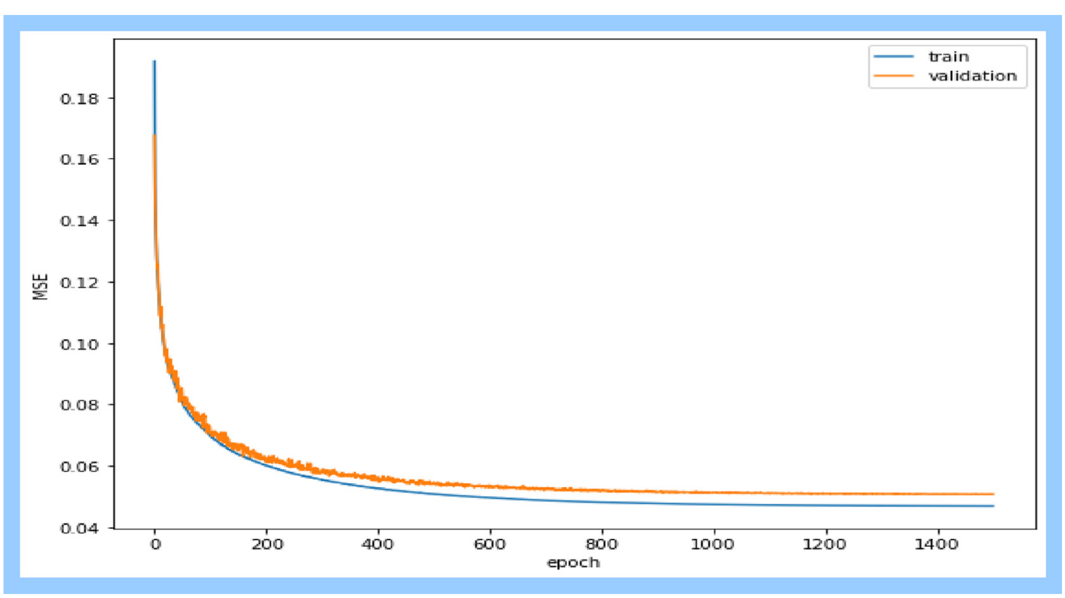

Fig. 16. History of train loss and validation loss in every epoch.

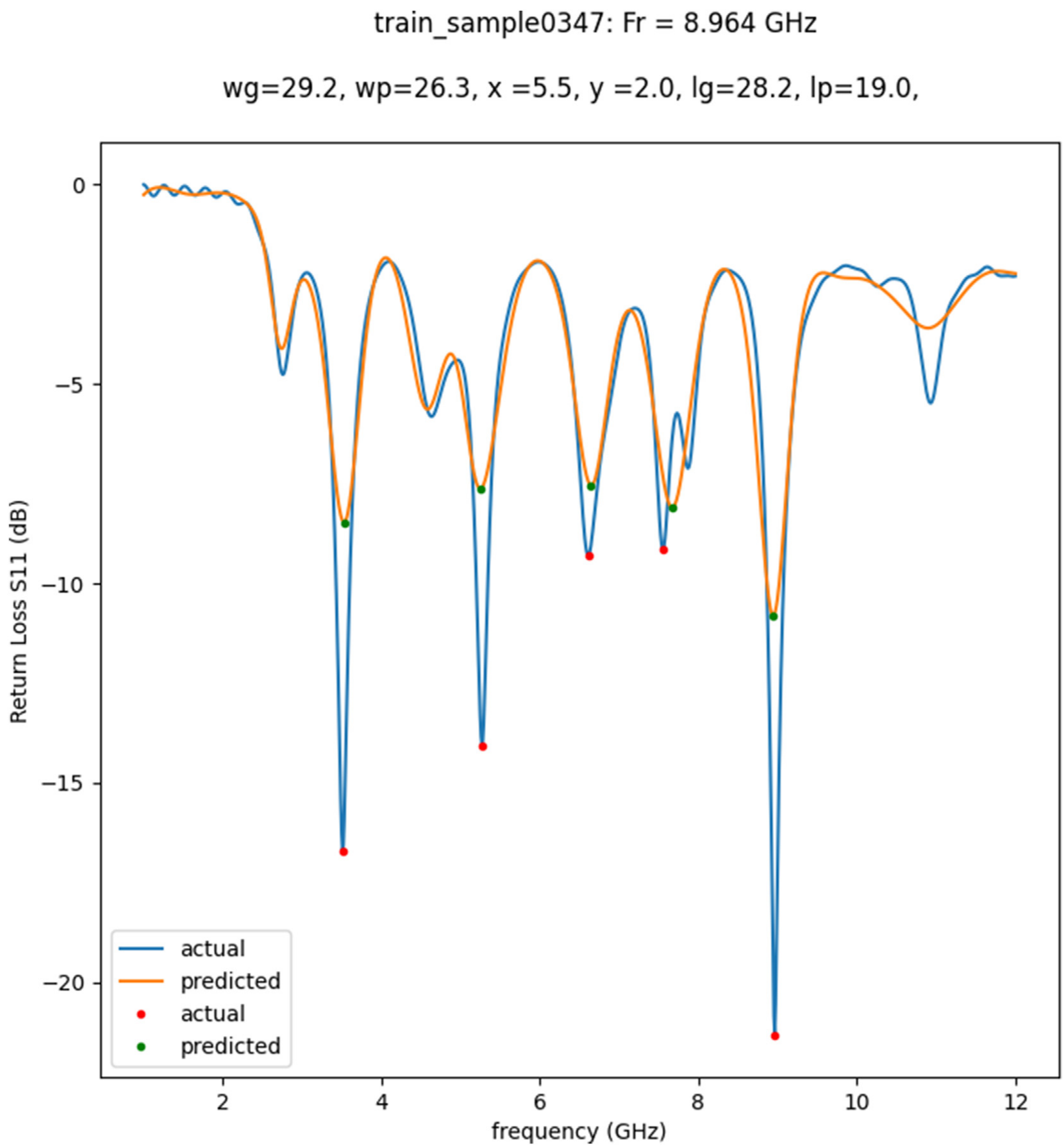

Fig. 17. Train sample No. 347.

validation was applied during training by choosing 10% of the data randomly, then excluding that portion from fitting process, and at the end of the epoch, the loss is computed for the excluded entries.

It is noticeable that the model reached a steady state after approximately 800 epochs (Fig. 16).

3. Results

Visual assessment shows good fitting performance of the proposed model for both training and testing instances.

3.1. Samples of training set

Figs. 17 and 18 refer to samples of the train data set, and Figs. 19 and 20 refer to the test data set.

3.2. Samples of testing set

To evaluate the model performance, multiple metrics were proposed and discussed, depending on the practical target of the regression process. For example.

(1) The error of S_{11} estimation (Table 2)
(2) The error in peak frequency positions

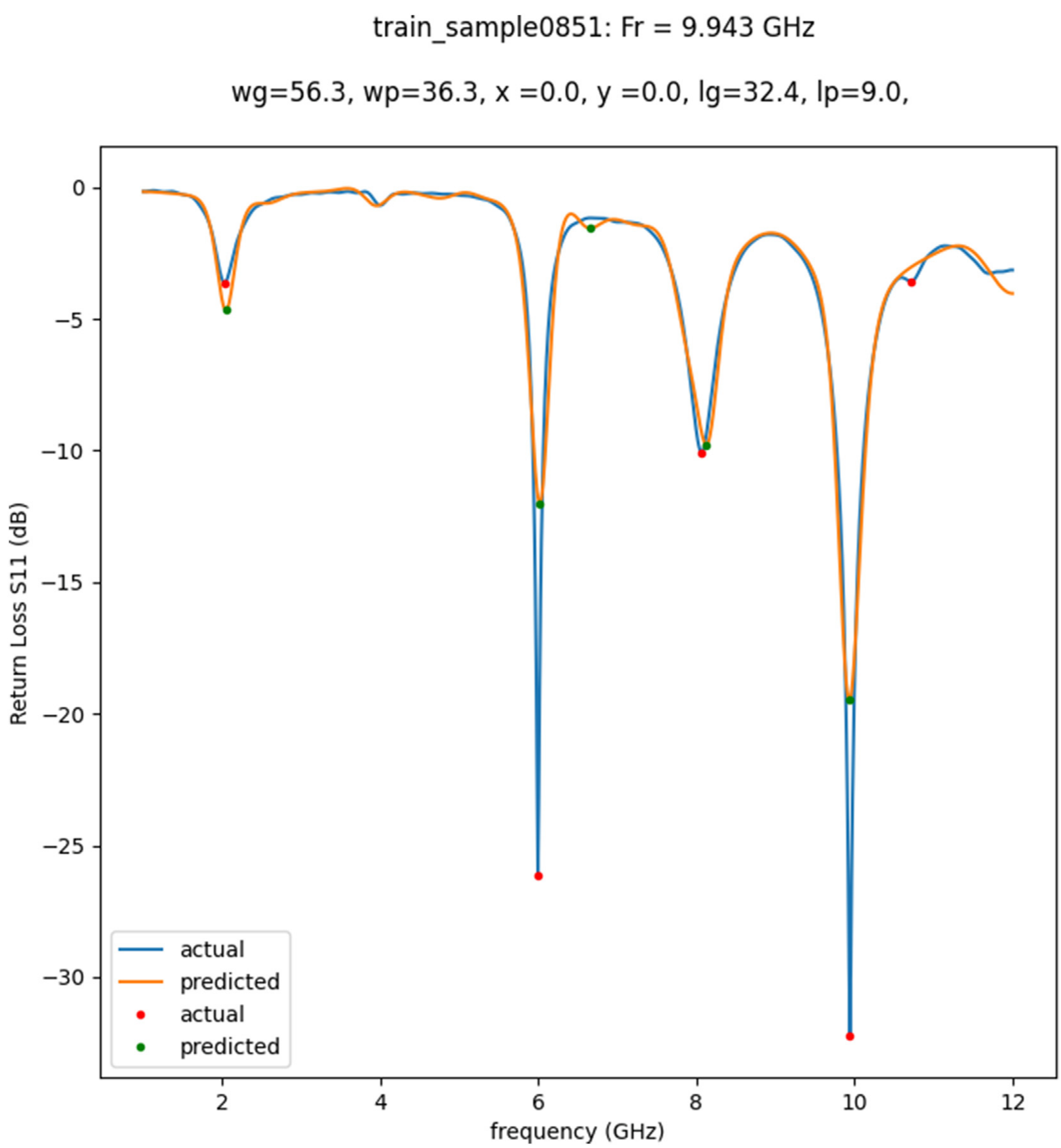

Fig. 18. Train sample No. 851.

(3) The hit ratio of the top-k resonance frequency.

The error of S_{11} estimation:

Although the absolute error is relatively small, the relative error tends to be large because there are a lot of small values that effect on the sensitivity of the fraction.

$$RE = \frac{|y - \hat{y}|}{|y|} \tag{3}$$

The hit ratio of the top-k resonance frequency.

(1) One possible evaluation metric of the proposed model is to measure its accuracy in detection of resonance frequencies of some antenna.
(2) A specific procedure was implemented for this mission which consists of several steps:
   (a) Define resonance frequency as the peak value in the S_{11} curve for the antenna. As there are a lot of such peaks, the top $k = 5$ peaks were selected (the peaks with largest S_{11} values).
   (b) Compute the frequencies of the top k peaks for both of the curves: the actual curve and the predicted curve.

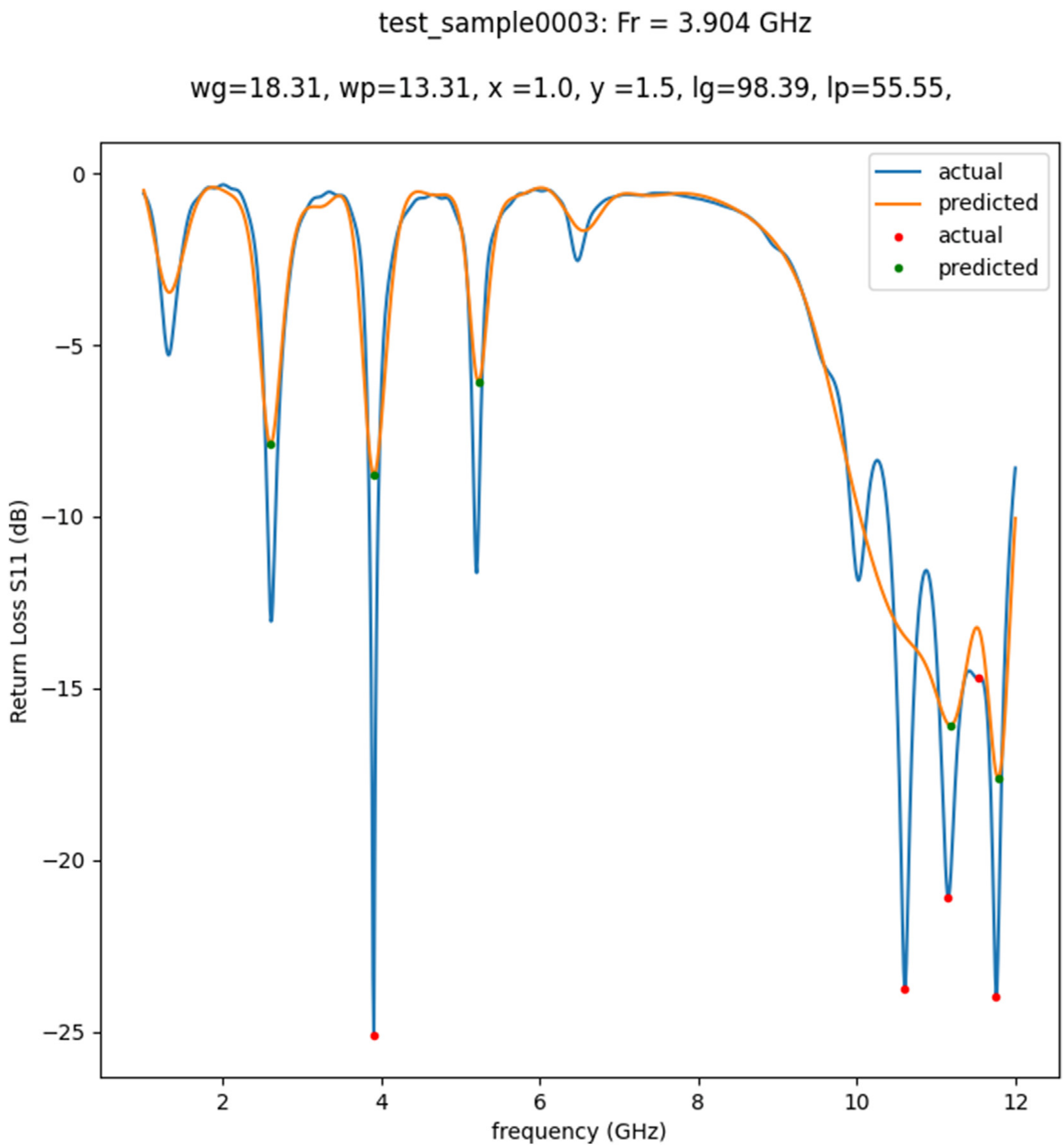

Fig. 19. Test sample No. 3.

(c) Create a distance matrix between the actual and predicted frequencies.
(d) Two frequencies are considered a ‘hit’ if the difference between them is less than some tolerance $tol = 0.2$GHz

For values $k = 5, tol = 0.2$ the average hit ratio over the training set was 3.62 out of 5 peaks, and on testing set was 3.45 out of 5.

The error in peak frequency positions:

The mean error of the detected peaks was 0.144 GHz on train set, and 0.116 GHz on test set.

Table 3 contains a comparison of this work with related literary works. This comparison demonstrates that the suggested antenna has number of inputs, number of outputs, no of samples, activation function, no of hidden layers and neurons, no of epoch, learning rate and error.

One sample option is to train an ML model that learns resonant frequency directly for a given geometric structure (Kushwah and Tomar, 2009; Kantipudi et al., 2021; Singh, 2015) However, most of these models generate fine predictions in a limited region of the space of physical dimensions of the antenna.

In this work, we propose a customized artificial neural network (ANN) model that approximate the full frequency response (S11 loss) as a function of frequency given the mechanical characteristic of the antenna at various forms of rectangular patch antenna (Fig. 2).

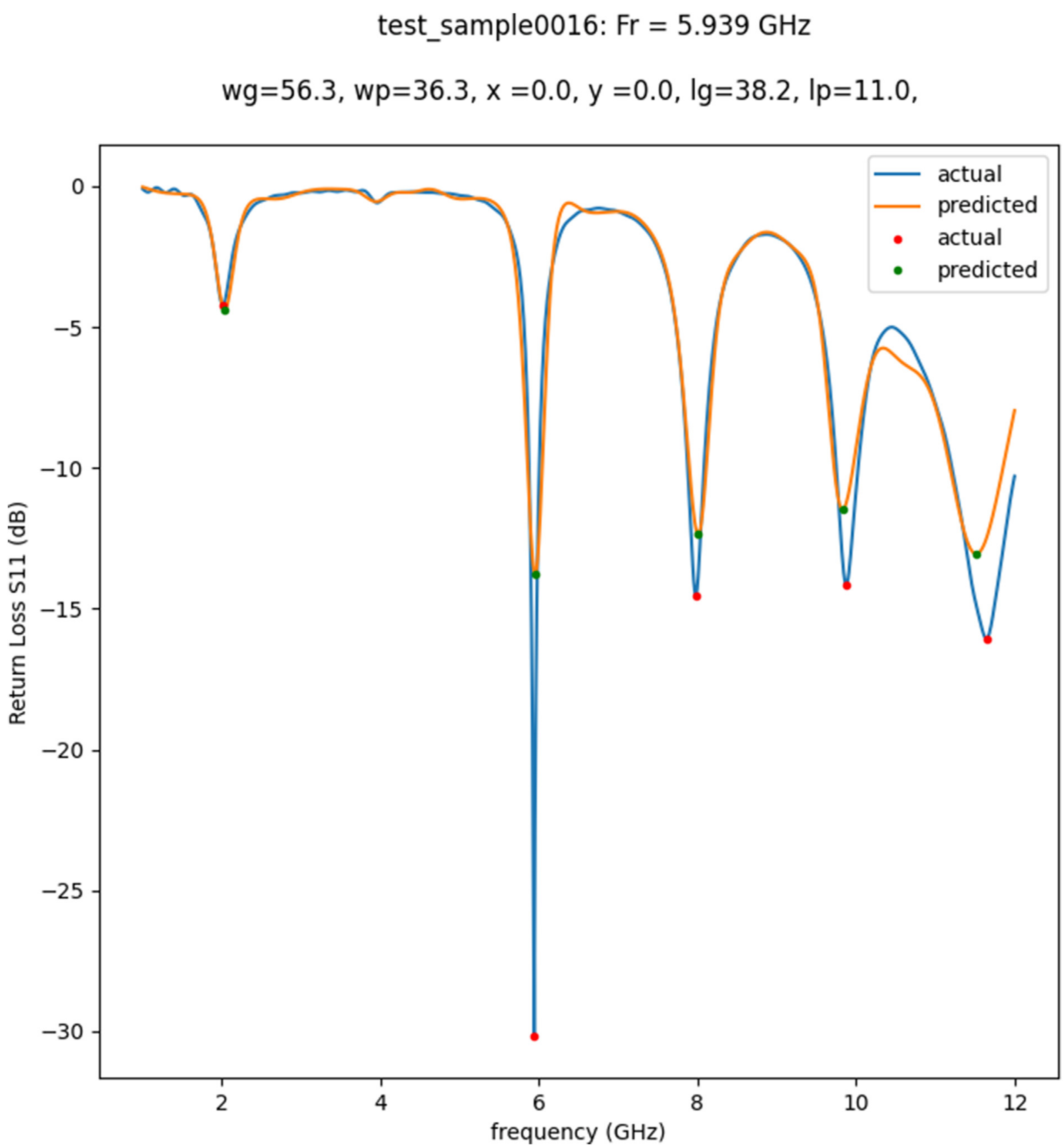

Fig. 20. Test sample No. 16.

Table 2. The error of S_{11} *estimation.*

Metric	train	test
Relative error RE	11.2%	11.9%
Mean Absolute Error (MAE)	0.99 dB	1.02 dB
Root Mean Squared Error (RMSE)	1.86 dB	1.91 dB

Table 3. A comparison of the suggested structure and related literary works.

References	Number of inputs (parameters)	output	Number of samples	Activation function	Number of hidden layers &neurons	Number of epoch	Learning rate	Error
Kantipudi et al. (2021)	5 inputs WL ξr (ξx&ξy) h	fr	90 samples 45 for training 45 for testing	MLP RBF	2 hidden layer (10&5 neurons)	450	0.1	0.01 training
Kushwah and Tomar (2009)	2 inputs If W, L fr	fr W, L	60 samples 45 for training 15 for testing	MLP RBF	2 hidden layer (10&5 neurons)	100	0.1	0.01 training
Singh (2015)	4 inputs W, L ξr, h	fr	320 samples 160 for training 160 for testing	RBF	1 hidden layer (20 neurons)	160	0.4	3.49886e-14 training
This work	7 inputs Wg, Wp Lg, Lp x, y, fr	s11	1733 samples 1300 for training 433 for testing	Linear RBF	3 hidden layer (200&200&1)	1500	**0.003** To 0.005	0.114 GHZ training0.116 GHZ testing

3.3. Conclusion

This work proposes a novel design of a microstrip patch antenna based on a neural network algorithm. We build, train, and evaluate our model using a dataset consists of the return loss response of 1733 different antennas, collected through simulation (CST). Most traditional machine learning models failed to achieve good performance for our task, and standard MLP networks do not fit as well. We proposed a custom model for this task. The overall architecture of the model is a sum of trainable Radial Based Functions RBFs. The mean error in detection of resonance frequencies (return loss peaks) was 0.144 GHz on train set, and 0.116 GHz on test set.

Author contribution

Ahmed A. Kabeel: Conception or design of the work; Methodology. Hadeer A. Shoeab: Data collection and tools; Data analysis and interpretation; Funding acquisition; Resources; Software; Drafting the article. El Said A. Marzouk: Methodology. Mohamed. A. Mohamed: Project administration; Supervision; Critical revision of the article; Final approval of the version to be published.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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المخلص

باستخدام الشبكات العصبية الاصطناعية ، وقد تم توضيح ذلك microstrip فى هذا البحث، تم اقتراح إجراء تصميم عام للهوائيات باستخدام هندسة التصحيح المستطيل. تم تحليل النموذج لـ 1733 مجموعة بيانات من معلمات الإدخال والإخراج. 1300 عينة للتدريب لإنشاء وتنفيذ نموذج خوارزمية Python و 433 عينة للاختبار و 1500 عصر بمعدل تعلم من (0.003 إلى 0.005). تم استخدام كان متوسط الخطأ 0.144 فى اكتشاف متوسط الخطأ (ذروه خسارة العوده) جيجاهرتز في مجموعة التدريب ، و 0.116 .ANN جيجاهرتز في مجموعة الاختبار. يتم تحسين مخرجات وظيفة الأساس الشعاعي عن طريق تغيير عدد الخلايا العصبية والطبقات المخفية. تمت مقارنة نتائج الطريقة المقترحة مع نتائج CST ووجدت أنها متوافقة جيدًا.