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Estimation of Scattering Parameters of U-Slotted Rectangular RFID Patch Antenna with Machine Learning Models

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Abstract
In this study, machine learning-based models have been used to estimate the return loss parameters of the operational resonant frequency of the U-slotted UHF RFID antenna. The data set utilized, consisting of 544 instances, has been collected from the simulation software as a consequence of the parametric evaluation of the antenna design parameters. Distinct machine learning methods have been used on two different types of output data, complex and linear scattering parameters, and the models' prediction performance has been evaluated. In the single-output regression models, a mean-square error value of 0.25% with an R^2 value of 95.54% was obtained with the Random Forest regression model, and a mean-square error value of 0.85% has been obtained with an R^2 value of 91.32% in the multiple-output regression technique.
Keywords: Machine learning, radio frequency identification, regression, RFID, scattering parameters.

1. Introduction

Machine learning methods have been used frequently in many fields such as science, economics, engineering, and healthcare. Machine learning is a powerful tool that can be used to predict desired data with statistical and mathematical methods. Like machine learning, antenna design is also carried out as a result of many mathematical and statistical studies. The dimensions and weights of wireless systems have shrunk due to advancements in circuit technology, and as a result, antennas, which are crucial parts of wireless systems, have downsized. Antenna designs are often created using 3D electromagnetic simulation software. These applications offer verified antenna performance data by employing the required mathematical methodologies. Many pieces of information, such as an antenna's return loss, far field results, input impedance value, gain, and radiation pattern, may be acquired using 3D electromagnetic simulation tools. As previously stated, because the antenna design is the result of several mathematical and statistical methods, the time spent by simulation programs to provide the necessary performance data increases as the complexity of the antenna topology increases. Also, while designing the antenna, many parametric studies are also carried out. However, with data sets created correctly with machine learning techniques, accurate result data can be obtained in a shorter time. For this reason, the motivation of this study is to save time while determining the optimum design in complex structures by using different machine learning models. While performing the study, an RFID (radio frequency identification) antenna design has been chosen. RFID antennas are used with RFID systems to identify the desired object, person, or any device. As a general structure, an RFID tag containing an RFID antenna is placed on an object to be identified or tracked. The end user obtains the necessary information about the object by providing the necessary communication with the RFID reader and another RFID antenna connected to this reader. In the literature, there are examples of antenna design with artificial intelligence methods such as machine learning [1], [2], artificial neural networks, and deep learning.

In the study conducted by Muñiz et al., [3], the SVR technique has been used for estimating the antenna array design in 2016. In 2019, Khan et al. [4] used a machine learning algorithm to optimize the slot width and length in a microstrip antenna structure by taking into account the near-field radiation of antennas. Fei-Yan et al., in 2018, have used the SVM technique based on density optimization and hybrid kernel function for modeling the antenna operating resonant frequency [5]. Deep learning studies have produced substantial excellent outcomes in feature extraction and classification; [6], [7] and provided a high advantage over manual feature extraction and classification algorithms. In addition, deep learning algorithms have also been used in segmentation [8], [9], multi-object tracking [10], [11], and biomedical [12], [13] applications. To give an example for biomedical applications, Phasukkit et al. [14] proposed a triple coaxial-half-slot antenna scheme with deep learning-based temperature prediction for hepatic microwave ablation. In 2020, machine learning models were used for estimating the scattering parameters of RFID antenna by Akdag et al. [15]. In the study conducted by Koziel et al. in 2021 [16], a novel approach to global optimization of multi-band antennas has been presented. The main component of the framework in the study is the knowledge-based inverse surrogate constructed at the level of response features. With this study, the average optimization cost is only 150 full-wave antenna analyses while ensuring precise allocation of the antenna resonance at target frequencies. Also, in literature, there are studies for optimization

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methods with the simulation-driven antenna design procedure. In 2021, Zhou et al. [17] presented work about a trust-region parallel Bayesian optimization method for simulation-driven antenna design problems. The Bayesian optimization method has also been used by Calik et al. in 2021 [18] for modeling frequency selective surfaces with the fully-connected regression model for automated architecture determination and parameter selection. In 2021, Koziel et al. [19] presented the improved modeling of microwave structures using performance-driven fully-connected regression surrogates. With surrogates, simulation-driven design procedures can be accelerated, and the CPU cost of electromagnetic analyses can be decreased.

As a result, different artificial intelligence and machine learning models have been used frequently in the field of antenna design, as in many areas in the literature, and provide reliable data.

2. Methodology

In this section, the antenna design and input-output data used in these models are presented together with the machine learning models. While the input parameters in the models are the antenna design parameters, the output parameters are the linear and complex states of the scattering parameter S_{11}. Also, detailed information about the data set created for the antenna is given in this section.

2.1. U-Slotted RFID Antenna Design

The antenna design used in the study was obtained through the Antenna Magus program. Antenna Magus has a dataset with many antenna design data in it and verified models can be simulated by importing them into CST Studio Suite. Because of their simplicity and compatibility with circuit board technology, microstrip antennas, also known as patch antennas, are highly common in the microwave frequency range. One of the most utilized microstrip antennas is the pin-fed rectangular patch employed in the study. The necessary parameters for antenna design have been presented in Figure 1.

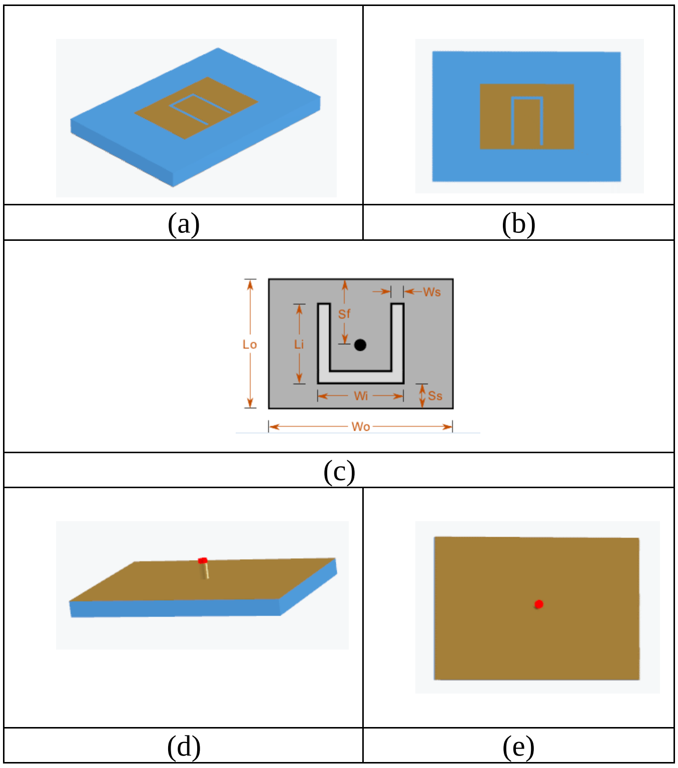

Figure 1. *Proposed antenna design; a) Perspective view of the antenna, b) Top layer of antenna, c) Design parameters of antenna top layer, d) Bottom perspective view of the antenna, e) Bottom view of the antenna.*

The top layer of the antenna design (Fig. 1.a and Fig. 1.c) contains the radiating part of the U-slot patch antenna. In the obtained antenna design, PEC material with a thickness of 0.035 mm was used as the conductor, and the thickness of the substrate material is 2.8 mm. The antenna's operating frequency can be changed by adjusting the length of the patch on the antenna. At the same time, the width of the patch has an effect on the antenna bandwidth.

The bandwidth of the antenna can be changed with the length of the U-shaped slot structure on the patch antenna. For the ground structure of the antenna, PEC material with the same thickness has been used and placed in such a way that it covers the same area as the substrate material. The design parameters of the antenna have been shown in Table 1 in detail.

Table 1. *Proposed antenna design parameters*

W_i	L_i	S_s	W_s	W_0	L_0	D_f	H_s
5.83	10.12	2.6	0.57	19.4	13.5	1.52	2.8

2.2. U-Slotted Patch RFID Antenna Design Scattering Parameters Machine Learning Algorithms

A data set has been created for U-slotted patch RFID antenna design with parametric studies, and the detailed data set has been presented in Table 2. While the geometric parameters of the antenna have been used for input data, the scattering parameter calculated for related input has been used for output data.

Table 2. *Antenna Design Parameters Data Set*

Parameter		Step Size
W_i	[2 25] (mm)	1.5 mm
L_i	[10.12 10.13] (mm)	0.01 mm
S_s	[0 15] (mm)	1.2 mm
W_s	[0.2 1.2] (mm)	0.07 mm
W_0	[19.48 30] (mm)	2.6 mm
L_0	[6 30] (mm)	1.6 mm
Total Data	544	

The design parameters have been determined as in Table 2. Here, Wi is the width of the inner slot, and Li is the length of the slot, W_S is the thickness of the slot. W_0 and L_0 values indicate the outer length and width of the antenna, respectively. The S_S value indicates the distance of the slot from the lowest part of the patch on the antenna. The data set contains 544 data and is divided as 34%-66% as test and training data.

In the 3D electromagnetic simulation program, the return loss, S_{11} value of the antenna can be obtained in both linear and complex form. While the linear scattering parameter can be evaluated as a single value as the output value, the complex scattering parameter has two parts, imaginary and real. Therefore different machine learning models have been constructed for different types of output data. In Figure 2, input and output values are shown in a single-output machine learning model, while Figure 3 shows a multi-output machine learning model. In both models, the input values are the design parameters of the antenna, while in Figure 2, the output data is the linear scattering parameter, and in Figure 3, the output data is the complex scattering parameter. Polynomial Regression, Random Forest, Gradient Boosting, Bayesian Ridge, and Voting Regressor have been used for the single output machine learning model, and Multiple Output Regression method has been used for the multiple output machine learning model. The simulation performance of the U-slotted RFID patch antenna has been evaluated on 544 different data. As a result of these simulations, the S_{11} reflection coefficient data, which determines the operating frequency of the antenna, have been obtained. Scattering parameters have been obtained in two different types, linear and complex, and when the data set has been examined, it has been seen that the data were suitable for regression methods. Although the instance of data in the data set is small, better results can be obtained with regression models by expanding the data set with more simulations.

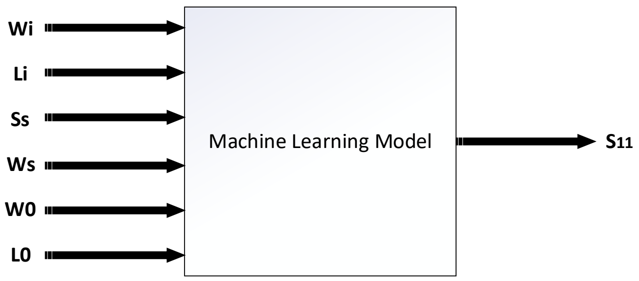

Figure 2. *Machine Learning model, input (RFID antenna design parameters), and output(linear scattering parameter value)*

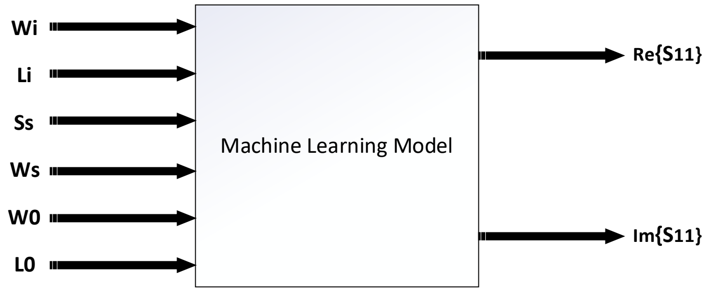

Figure 3. *Machine learning model, input (RFID antenna design parameters), and output (complex scattering parameter values)*

3. Numerical Results

The findings of the various approaches used for the machine learning models depicted in Figures 2 and 3 are provided in this section. Machine learning methods have been written in Python programming language with the Sci-kit Learn library, and the prediction performances obtained from different methods have been compared.

3.1. Regression results for single output S_{11} value

The estimation performance of different methods for the single output machine learning model of U-slotted RFID patch antenna design has been presented in this section. For seeing the estimation performance, 20 sample test instances have been used, and the actual and estimated output values have been presented for Polynomial Regression, Random Forest, Bayesian Ridge, and Gradient Boosting and Voting Regressor methods in Figure 4 – Figure 8, respectively.

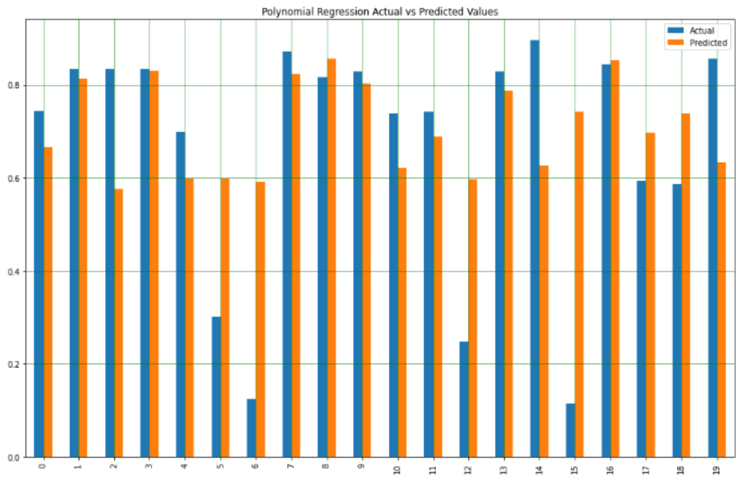

Figure 4. *Polynomial Regressor Actual / Estimated Data*

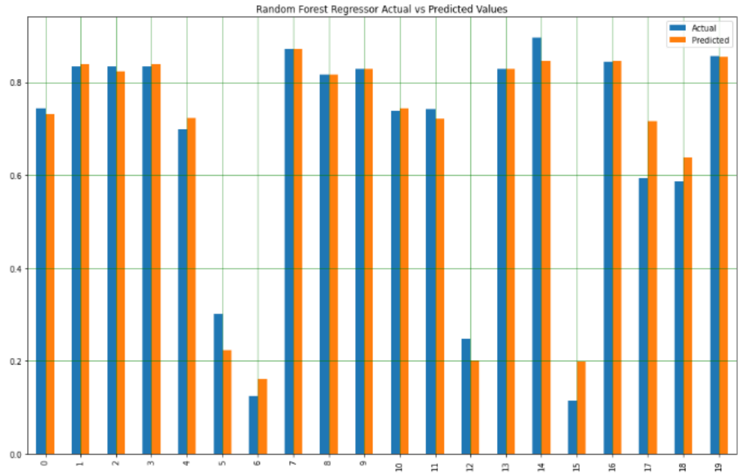

Figure 5. *Random Forest Regressor Actual / Estimated Data*

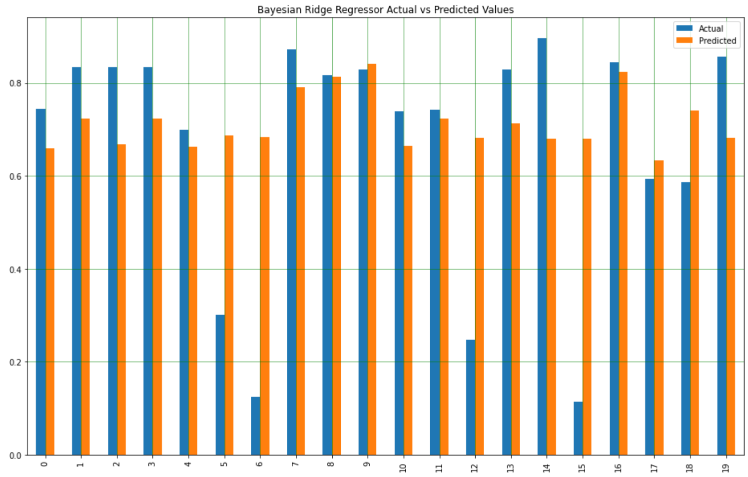

Figure 6. *Bayesian Ridge Regressor Actual / Estimated Data*

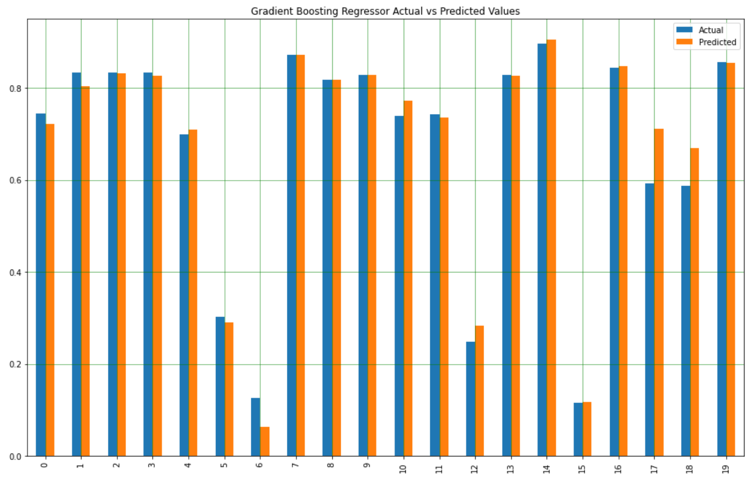

Figure 7. *Gradient Boosting Regressor Actual / Estimated Data*

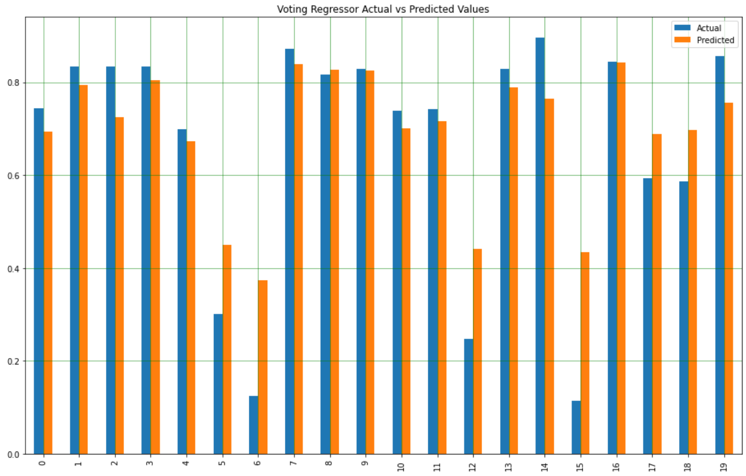

Figure 8. *Voting Regressor Actual / Estimated Data*

3.2. Regression results for multiple output complex S_{11} value

The estimation performance of the multi output regression method for S_{11} estimation of the presented U-slotted patch RFID antenna design is discussed in this section. Because the output value is composed of two data points, the Multi-Output (Figure 9) regression approach has been used. For 20 sample test instances, actual and estimated output values have been presented in Figure 9.

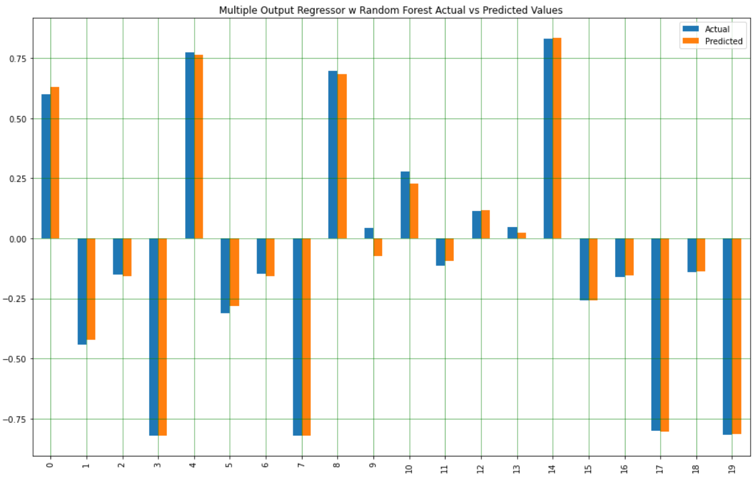

Figure 9. *Multiple Output Regressor Actual / Estimated Data*

4. Results and Conclusion

In this study, the estimation of the scattering parameters of a sample RFID antenna design obtained from the Antenna Magus program has been studied. The data set has been created by parametrically changing the input data in the antenna geometry with the help of a 3D electromagnetic simulation program and has a total of 544 instances. The scattering parameter data were obtained in two different forms, linear and complex. While the linear scattering parameter data has a single element, the complex scattering parameter has two parts, real and imaginary. For this reason, Polynomial Regression, Random Forest, Bayesian Ridge and Gradient Boosting methods are used for linear scattering parameter estimation, while multiple output regression method is used for complex scattering parameter estimation. The prediction performance performances obtained from single and multiple output machine learning methods are presented in detail.

Results	Polynomial Regressor
R2 Score %	18.2861811956603
Mean Squared Error %	4.621287953849866
Root Mean Squared Error %	21.497181103228087
Mean Absolute Error %	16.74708846728713
Maximum Error %	62.71797723250162
Results	**Random Forest Regressor**
R2 Score %	95.54023769162794
Mean Squared Error %	0.25221983422489297
Root Mean Squared Error %	5.022149283174415
Mean Absolute Error %	2.7945147333333327
Maximum Error %	36.18767999999999
Results	**Gradient Boosting Regressor**
R2 Score %	88.29153424072864
Mean Squared Error %	0.6621669695910813
Root Mean Squared Error %	8.137364251347492
Mean Absolute Error %	3.942763213148881
Maximum Error %	47.97144815549858
Results	**Bayesian Ridge Regressor**
R2 Score %	6.409634448190449
Mean Squared Error %	5.292960667480311
Root Mean Squared Error %	23.006435333359036
Mean Absolute Error %	17.724106280510114
Maximum Error %	58.29358260760041
Results	**Voting Regressor**
R2 Score %	76.21253383604501
Mean Squared Error %	1.3452893579642409
Root Mean Squared Error %	11.598660948420903
Mean Absolute Error %	9.07985815233816
Maximum Error %	38.64203616952579
Results	**Multi Output Regressor**
R2 Score %	91.3280284583893
Mean Squared Error %	0.8547496425562304
Root Mean Squared Error %	9.245267127326448
Mean Absolute Error %	4.448649173722576
Maximum Error %	---

Figure 10. *Regression models comparison table*

Table 3. *Multi-output regression technique test data and output values*

Input Parameters L_i,W_i,L_0,W_0,S_s,W_s	Estimated Output Parameters (S_{11}real,S_{11}img)	Actual Output Parameters (S_{11}real,S_{11}img)
[10.13,5,10,19.5,2.6,0.3]	[0.784904 -0.193443]	[0.799569 -0.117085]
[10.13,10,25,19.5,2.6,1.2]	[0.8240994 -0.2392208]	[0.826512-0.240428]
[10.12,6.5,13.5,19.48,2.5,0.65]	[0.124008 -0.089705]	[0.133303-0.123932]

When the estimation performances of different machine learning methods are examined, it is seen that the best estimation performance is obtained in the Random Forest method. Figure 10 includes the comparison of the estimation performances of all methods. Here, it is seen that the estimation performance is not good for Bayesian Ridge and Polynomial Regression methods. For this reason, it would be more appropriate to use the Random Forest method for the single output machine learning model. With the multiple output regression method, 91.32% R^2 value has been obtained. Table 3 presents the actual input and actual output / estimated output values for the sample data. However, expanding the number of instances in the data set used in this study will result in more precise results. At the same time, utilizing machine learning's predictive performance, these approaches may be applied to various antenna designs, as well as developing antenna calculation software.

Declaration of Interest

The authors declare that there is no conflict of interest.

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