

Machine Learning Based b-Shaped Monopole Antenna for RF Energy Harvesting Applications

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Abstract – In this paper, a machine learning (ML) based b-shaped multiband monopole antenna for RF energy harvesting system is presented. ML algorithms are used to optimize the antenna in order to reduce the simulation time and speed up the design process. Geometric parameters on the antenna have been determined as input in the ML model. There are two different output data: the complex and decibel magnitudes of the reflection coefficient (S11) parameters, which have been determined as output parameters. The dataset consists of 1890 samples in total. Initially, attempts were made to predict the decibel magnitude of reflection coefficient parameters using different ML algorithms, and these ML algorithms were compared with each other. Then, for the complex part of the reflection coefficient parameters, a Multi-Output regression model was applied to the real and imaginary values. The best results were obtained with the K-Nearest Neighbors algorithm for the decibel magnitude of reflection coefficient parameters, achieving a 0.14% RMSE value and a 99% R² value. The Multi-Output Regression algorithm was applied to complex (Real, Imaginary) values, achieving an R² value of 92.51% and a RMSE value of 0.10.

Keywords – Machine Learning, RF Energy Harvesting, Antenna Design, Monopole Antenna, Wireless Electronic Devices

I. INTRODUCTION

In order to meet the energy needs in the use of electronic devices, non-renewable energy sources such as fossil fuels are mostly used and these fuels are highly harmful to the environment (greenhouse effect, acid rain, etc.) [1]. Therefore, researchers have been researching new eco-friendly renewable energy sources.

Due to the increased use of mobile devices such as televisions, cell phones, and Wi-Fi, the availability of RF signals in the atmosphere has significantly increased. These devices communicate via RF power transmission, with most of the energy they emit being wasted. RF energy transmission dates back to the experiments of Heinrich Hertz, in the 1880s [2]. RF signals can carry power between 0.02 μ W/cm² and 1 μ W/cm² [3].

Table 1. Various ambient sources in the surrounding [3].

Ambient Sources	Sensors Used	Availability	Power Density	Output Voltage
Thermal	Thermo-electric converters	Continuous	40 μ W/cm ² - 100 μ W/cm ²	10 MW - 100MW
Wind	Wind turbines	Continuous	3.5mW/cm ²	100MW and above
Solar	Photo-voltaic solar panels	Day Time	1500 μ W/cm ² outdoor daylight	0.5V-1V
Vibration	Piezo-electric	Activity - Dependent	3.8 μ W/cm ² - 500 μ W/cm ²	10-25V
Electro-magnetic (EM)	Rectenna	Continuous	0.02 μ W/cm ² - 1 μ W/cm ²	3-4V

RF energy harvesting system is based on the idea of how to recycle wasted RF signals. RF energy harvesting system converts the RF signals in the surrounding environment into DC output voltage using antenna, matching circuit and rectifier circuit. Antenna plays a very important role as it harvests the RF signals in the surrounding environment [4].

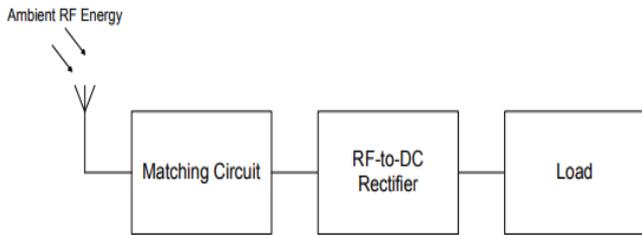


Fig 1 Block diagram of RF energy harvesting system [5]

The matching circuit acts as a bridge by minimizing the impedance mismatch between the antenna and the rectifier circuit [6]. Finally, the rectifier circuit converts the received RF signal to DC voltage that can be used to power the wireless device or charge the battery [7]. Compared to other ambient sources, RF power density is very low. Therefore, RF energy harvesting system requires an antenna capable of high efficiency harvesting.

There are many literature studies on RF energy harvesting system. Mustafa Cansız measured DC output power levels and power efficiency at different RF power levels using the P2110-EVB module from Powercast, which is used as an RF energy harvesting circuit [8]. He calculated the

highest power efficiency ratio as 56.92% at 5 dBm RF power level and the lowest power efficiency ratio as 45.60% at 0 dBm RF power level. It was determined that the RF energy harvesting module was able to harvest approximately half of the incoming power in response to RF input power levels ranging from 0 dBm to 10 dBm, at a carrier frequency of 915 MHz. Antennas are designed with electromagnetic simulation programs, and the simulation time increases as the antenna geometry designed in these programs becomes more complex [9]. ML algorithms have the potential to speed up the antenna design process, reduce simulation times, and enhance the overall performance of the system [10]. Ömer Selim YAŞA et al. predicted the reflection coefficient of the designed antenna using ML algorithms. Six parameters are defined as input and the data set consist of 486 samples in total. In regression methods where the magnitude of the reflection coefficient is used as the output data, the best results have been obtained with increased gradient-boosting regression, achieving an R² value of 97.77% and an RMSE value of 0.096% [11]. In addition, Jana Álvarez Muñoz et al. applied the support vector regression model to predict the antenna array [12].

In this paper, a ML based multiband monopole antenna design used for RF energy harvesting system is presented. In Section II, information about the design parameters of the proposed antenna and the ML methods planned to be implemented for these parameters is presented. In Section III, the results of the proposed antenna and performance data of the ML models are explained. In Section IV, discussion is conducted. In Section V, the study result is summarized.

II. MATERIALS AND METHOD

In this section, the features and design parameters of the proposed antenna are presented. Also, the machine learning models used to predict the reflection coefficient at 2.45 GHz are presented. In order to use machine learning algorithms correctly, a consistent and formalized data set is required. Information about the data set used is given in this section.

A. Proposed Antenna Design

There are various antenna designs used for RF energy harvesting systems [13],[14],[15]. In this study, a ML based b-shaped multiband monopole

antenna designed. The proposed antenna is printed on a FR-4 substrate with a dielectric constant of 4.3, loss tangent of 0.025 and thickness of 1.6 mm. Annealed copper is used as ground and patch materials with 0.035 mm thickness.

Many geometric parameters can be determined on the proposed antenna, thus increasing the number of input parameters for ML algorithms. The operating frequency and bandwidth of the antenna can be modified by changing the dimensions of the patch and the ground surface of the antenna. The proposed antenna model numerically computed.

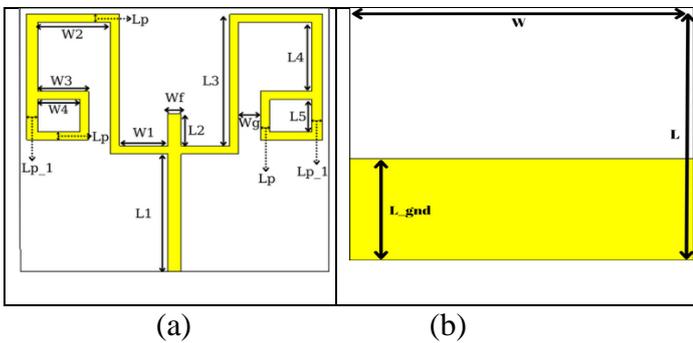


Fig. 2 Proposed antenna design; (a) Front side, (b) Back side

Table 2. Parameter of proposed antenna (mm)

W	Wf	W1	W2	W3	W4	Wg	L_gnd
70	3	11	16.5	11.5	9.5	5	26
L	L1	L2	L3	L4	L5	Lp	Lp_1
65	29	8	32.5	17	8	2	2.5

B. Predicted Reflection Coefficient Parameters Using Machine Learning Algorithms

The reflection coefficient results of the proposed antenna according to different geometrical parameters have been numerically calculated. The geometrical parameters changed in proposed antenna were determined as W1, W4, L3 and L5 (Fig. 2). The antenna design parameters data set is present in Table 3.

Table 3. Proposed antenna design parameters dataset

Parameter	Change Rate (Unit)	Step Size	Number of Samples
W1	[-1.5 11.5] (mm)	3	5
W4	[-6 12] (mm)	3	7
L3	[10 33.5] (mm)	3	9
L5	[0 10] (mm)	2	6
Total Data			1890

The simulation performance of proposed antenna is realized on 1890 data and the reflection coefficient parameter of the antenna's input port was obtained. Two different reflection coefficients were obtained: complex (S11-Real, S11-Imaginary) and decibel (S11-dB) reflection coefficient. Therefore, two different ML models were designed to compare the performances. We used 20% of the dataset as the test set and 80% as the training set.

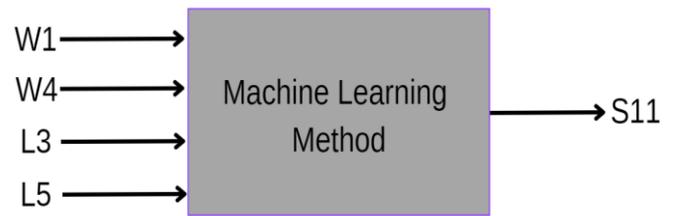


Fig. 3 Machine learning model for reflection coefficient.

First ML model is used to predict decibel reflection coefficient parameters with the input parameters of W1, W4, L3, L5 and the output parameter of S11-dB through several algorithms including Linear Regression, Decision Tree, Random Forest, Polynomial Regression, and the K-nearest neighbors algorithm. Additionally, artificial neural networks (ANNs), which have the capability to solve complex problems, were implemented, and a performance comparison was conducted.

Second ML model is used to predict real and imaginary reflection coefficient parameters with the same input parameters and the output parameters of S11-Real and S11-Imaginary. Multi-output regression algorithms were applied to this ML model since there are two outputs in the dataset.

III. RESULTS

This section presents the results of the proposed antenna and ML models. The proposed antenna was designed using numerical computation software, and the regression algorithms mentioned in Section II were developed in Python. The performance comparisons are also presented.

A. Simulation Results of Proposed Antenna

The antenna has a bandwidth of 1.72 GHz - 3.02 GHz and 3.47 GHz - 4.79 GHz and operates

effectively at the commonly used frequencies GSM1800, UMTS 2100, WLAN 2450 and LTE 2600 (Fig. 4). The gain values of the designed antenna were calculated numerically as 3.28 dBi at 1.8 GHz, 3.68 dBi at 2.1 GHz, 4.46 dBi at 2.45 GHz and 4.75 dBi at 2.6 GHz, respectively. The designed antenna has four resonant values at frequencies of 1.95 GHz, 2.84 GHz, 3.67 GHz and 4.49 GHz. The reflection coefficient values of proposed antenna are -29.17dB at 1.95GHz, -20.34dB at 2.84GHz, -14.67dB at 3.67GHz and -36.75dB at 4.49GHz.

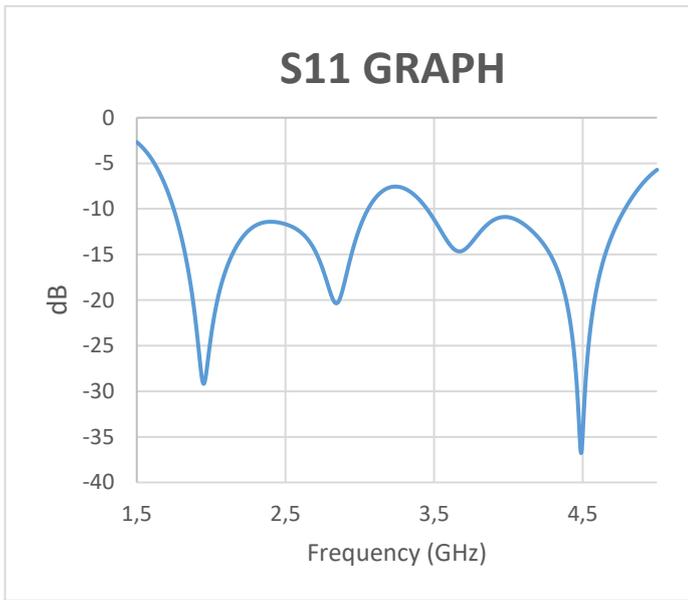


Fig.4 S11 graph of proposed antenna

Farfield parameters at 1.8 GHz, 2.1 GHz, 2.45 GHz and 2.6 GHz are summarized in Table 4. Also, 3D radiation patterns for 1.8 GHz, 2.1 GHz, 2.45 GHz, 2.6 GHz are given in Figure 5.

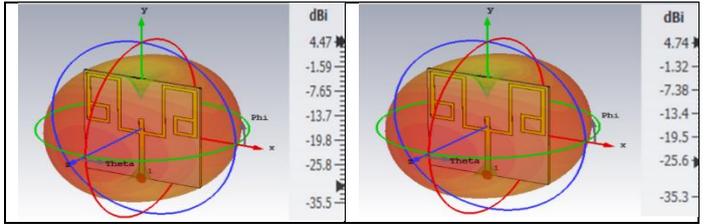


Fig. 5 Simulated 3D radiation pattern for the antenna at (a) 1.8 GHz, (b) 2.1 GHz, (c) 2.45 GHz, (d) 2.6 GHz.

Table 4. Gain, S11 and Efficiency values

Frequency (GHz)	Gain (dBi)	S11 (dB)	Radiation Efficiency	Total Efficiency
1.8 GHz	3.28 dBi	-13.08 dB	%90	%85
2.1 GHz	3.84 dBi	-16.67 dB	%91	%89
2.45 GHz	4.47 dBi	-11.48 dB	%90	%84
2.6 GHz	4.74 dBi	-12.51 dB	%89	%84

B. Machine Learning Algorithms Performance Data for Decibel Reflection Coefficient Prediction

The prediction results of the decibel reflection coefficient parameter of the proposed antenna design according to different ML algorithms are presented in this section. Linear Regression, Decision Tree, Random Forest, Polynomial Regression, Artificial Neural Network and K-Nearest Neighbors algorithms were applied, respectively. Table 5 presents the comparison of the best ML algorithms applied for the decibel reflection coefficient output parameters.

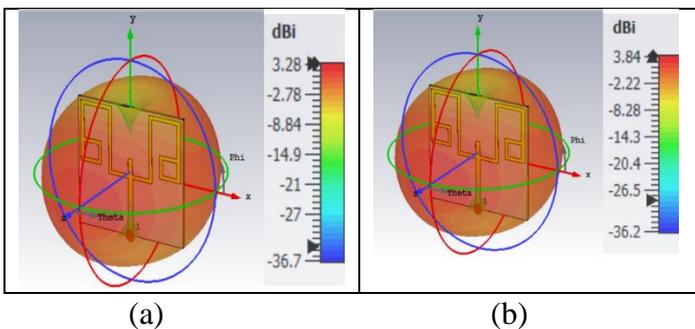


Table 5. Selected Machine learning algorithms

Results	Decision Tree
R ² Score %	0.997
Mean Squared Error %	0.0458
Mean Absolute Error %	0.0514
Root Mean Squared Error %	0.214
Results	Random Forest
R ² Score %	0.999
Mean Squared Error %	0.021
Mean Absolute Error %	0.037
Root Mean Squared Error %	0.145
Results	K-Nearest Neighbors
R ² Score %	0.999
Mean Squared Error %	0.019
Mean Absolute Error %	0.031
Root Mean Squared Error %	0.138

C. Machine Learning Algorithms Performance Data for Complex Reflection Coefficient Prediction

Complex reflection coefficient parameters consist of two output data points. Therefore, a Multi-Output regression model, which can predict these complex reflection parameters using double output data is utilized. In Table 6, the performance data of the Multi-Output-Regression algorithm is presented. In addition, Table 7 presents the comparison of test input data and predicted output data with actual output values for the Multiple Output regression algorithm.

Table 6. Multi-Output Regression algorithm performance data

Results	Multi-Output Regression
R ² Score %	0.925
Mean Squared Error %	0.011
Mean Absolute Error %	0.073
Root Mean Squared Error %	0.105

Table 7. Input test data and output results for Multiple-Output Regression algorithm

Input Parameters (W1,L5,W4,L3)	Predicted Output Values (S11-Real,S11-Im.)	Actual Output Values (S11-Real,S11-Im.)
[4.5,0,12,31]	[0.398, 0.067]	[0.397, 0.105]
[-1.5,8,12,33.5]	[0.394, 0.445]	[0.400, 0.430]
[7.5,2,9,22]	[0.522, -0.002]	[0.509, 0.003]
[1.5,10,9,19]	[0.574, 0.537]	[0.567, 0.710]
[11.5,10,12,33.5]	[0.177, 0.100]	[0.117, 0.239]

IV. DISCUSSION

In this study, performance data from different ML algorithms are presented for the prediction of the reflection coefficient parameter of the proposed antenna used for RF energy harvesting system. Two different data types the reflection coefficient parameter were obtained from the simulations. For the decibel reflection coefficient parameter, Linear Regression, Decision Tree, Random Forest, Polynomial Regression, ANN's and K-Nearest Neighbors algorithms that can predict with single output data were applied, while Multi-Output regression algorithm that can predict with double output data was used for the complex reflection coefficient parameter consisting of double output values.

CONCLUSION

In this paper, machine learning based multiband monopole antenna using for RF energy harvesting applications is presented. The proposed antenna can harvest the widely used in communication. In addition, there are four resonant frequency. When the results of the test data are examined, it is seen that the best prediction performance is obtained in the K-Nearest Neighbors algorithm. However, it is observed that the performance data of the Random Forest algorithm is very close to the performance data of the K-Nearest Neighbors algorithm. Also 0.9251 is obtained for R² from the Multiple-Output regression method.

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REFERENCES

- [1] Adedibu, P. A., Animasaun, D. A., & Joseph, G. G. (2021). Exploring the potentials of microalgae as an alternative source of renewable energy. *Nigerian Journal of Biotechnology*, 38(1), 24-39.
- [2] Visser, H. J., & Vullers, R. J. (2013). RF energy harvesting and transport for wireless sensor network applications: Principles and requirements. *Proceedings of the IEEE*, 101(6), 1410-1423.
- [3] Mohanta, H. C., & Akwafo, R. An Overview on RF Energy Harvesting Techniques for Low Power Sensors in Wireless Communication Systems.

- [4] Jung, J., & Kwon, I. (2022). A capacitive dc-dc boost converter with gate bias boosting and dynamic body biasing for an rf energy harvesting system. *Sensors*, 23(1), 395.
- [5] Khansalee, E., Zhao, Y., Leelarasmee, E., & Nuanyai, K. (2014, May). A dual-band rectifier for RF energy harvesting systems. In *2014 11th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON)* (pp. 1-4). IEEE.
- [6] Bonnin, M., Song, K., Traversa, F. L., & Bonani, F. (2023). Stochastic analysis of a bistable piezoelectric energy harvester with a matched electrical load.
- [7] Inbaraj, D., Kailasam, M., & Sankararajan, R. (2022). Statistical analysis of radiofrequency energy harvester with bandpass filter for ultra-low power applications. *International Journal of Numerical Modelling: Electronic Networks, Devices and Fields*, e3077.
- [8] CANSIZ, M. (2019). 915 MHz taşıyıcı frekansında RF enerji hasatlama. *Dicle Üniversitesi Mühendislik Fakültesi Mühendislik Dergisi*, 10(1), 91-98.
- [9] Tak, J., Kantemur, A., Sharma, Y., & Xin, H. (2018). A 3-D-printed W-band slotted waveguide array antenna optimized using machine learning. *IEEE Antennas and Wireless Propagation Letters*, 17(11), 2008-2012.
- [10] Ranjan, P., Yadav, S., Gupta, H., & Bage, A. (2023). Design and Development of Machine Learning Assisted Cylindrical Dielectric Resonator Antenna.
- [11] Akdağ, I., Yaşa, Ö. S., Göçen, C., & Palandöken, M. UHF Bandında Çalışan RFID Anten Tasarımının Geri Dönüş Kaybı Verilerinin Makine Öğrenmesi Teknikleri ile Tahminlenmesi. International Antalya Scientific Research and Innovative Studies Congress.
- [12] J. Á. Muñiz, R. G. Ayestarán, J. Laviada, and F. Las-Heras, "Support vector regression for near-field multifocused antenna arrays considering mutual coupling," *Int. J. Numer. Model. Electron. Networks, Devices Fields*, vol. 29, no. 2, pp. 146–156, 2016, doi: 10.1002/jnm.2058.
- [13] Fan, Y., Liu, X., & Xu, C. (2022). A Broad Dual-Band Implantable Antenna for RF Energy Harvesting and Data Transmitting. *Micromachines*, 13(4), 563.
- [14] Fang, L. H., Fahmi, M. I., Jordan, J. B. A. M., Kimpol, N. B., Aihsan, M. Z., & Muhsin, M. A. S. B. A. (2022, September). Development of T-Shaped Antenna for RF Energy Harvesting System. In *2022 IEEE International Conference on Power Systems Technology (POWERCON)* (pp. 1-6). IEEE.
- [15] Nadali, K., McEvoy, P., & Ammann, M. J. (2022, May). A Broadband Circularly Polarised Slot Antenna for Ambient RF Energy Harvesting Applications. In *2022 International Workshop on Antenna Technology (iWAT)* (pp. 153-156). IEEE.