Journal of Artificial Intelligence and Data Science (JAIDA)
e-ISSN: 2791-8335
https://dergipark.org.tr/pub/jaida

Vol. 4, No. 1, pp. 33-38, 2024
Research Article
Received: 08/05/2024 Accepted: 30/05/2024

Microstrip Antenna Design for 2.4 GHz RF Energy Harvesting Circuits with Artificial Neural Networks

Burak DÖKMETAŞ [1], Mehmet Ali BELEN [2,*]

Abstract
This study explores the synthesis of microstrip antennas designed for 2.4 GHz RF energy harvesting circuits through the integration of artificial neural networks (ANNs). Utilizing a 3D electromagnetic (EM) simulation tool, extensive datasets were generated for training and testing the ANN model. A meticulous trial-and-error process was employed to optimize critical hyperparameters, including the number of hidden layers, neurons per layer, and activation function types. The outcome of this process was the identification of an optimal ANN model, proficient in accurately capturing complex relationships between antenna design parameters and energy harvesting efficiency. The integration of the 3D EM simulation tool and the tuned ANN model facilitated a computationally efficient approach to antenna optimization, reducing reliance on resource-intensive simulations. This research contributes to the advancement of RF energy harvesting systems, showcasing the potential of artificial intelligence in streamlining the design process for optimal microstrip antennas in 2.4 GHz applications. The demonstrated methodology provides insights into the future of computational design, offering a swift and efficient path for meeting the evolving demands of wireless communication and sensor technologies.

Keywords: Microstrip Antenna; Artificial Neural Network; Optimization; 2.4 GHz; Energy Harvester.

1. Introduction

In recent years, the increasing demand for wireless communications and the expansion of Internet of Things (IoT) devices have focused researchers on this area [1]. Concurrently, the importance of efficient and sustainable energy sources is becoming increasingly critical. Traditional power solutions face limitations in terms of size, weight, and environmental impact, making Radio Frequency (RF) energy harvesting a promising alternative for powering these autonomous and energy-limited devices. RF energy harvesting systems utilize electromagnetic radiation from the environment and convert it into electrical power for a variety of applications, from wireless sensor networks to wearable devices [2-4]. The electromagnetic spectrum, particularly the 2.4 GHz frequency band, has gathered significant interest due to its widespread use in various communication standards such as Wi-Fi and Bluetooth. This frequency range not only provides extensive RF energy in urban and industrial environments but also aligns with the operating frequencies of many electronic devices, making it an ideal candidate for energy harvesting applications.

Especially, the design and optimization of microwave antennas for RF energy harvesting circuits present a challenging problem in the field of wireless communication and sensor technologies [5]. The pursuit of antennas with enhanced performance characteristics such as increased efficiency, compact size, and adaptability to various operating conditions has become critically important in meeting the demands of modern electronic devices. As the demand for wireless communication systems continues to rise, addressing the challenges associated with microwave antenna design is crucial for advancing the capabilities of these technologies.

*Corresponding author

BURAK DÖKMETAŞ: Kafkas University, Faculty of Engineering and Architecture, Electrical Electronic Engineering Department, Türkiye; e-mail: burak.dokmetas@kafkas.edu.tr; 0000-0001-5900-6691

MEHMET ALİ BELEN*; Iskenderun Technical Universtiy, Faculty of Faculty of Engineering and Natural Sciences, Electrical Electronic Engineering Engineering Department, Türkiye; e-mail: mali.belen@iste.edu.tr 0000-0001-5588-9407

One of the key challenges in antenna design lies in achieving optimum performance at specific frequency bands such as the commonly used 2.4 GHz range. The complexity of microwave propagation, material considerations, and the interaction of antenna parameters require a comprehensive approach to design and optimization. Traditional methods typically involve a time-consuming and iterative process that relies heavily on manual tuning and extensive simulations to achieve the desired characteristics [6].

To overcome these challenges and accelerate the design process, artificial intelligence (AI) techniques, especially artificial neural networks (ANNs), have emerged as effective tools for antenna optimization [7-11]. Inspired by neural networks in the human brain, ANNs excel at learning complex patterns and relationships within data, which makes them well-suited to handle the complex and nonlinear nature of antenna design problems [12-13]. ANNs can acquire knowledge from large datasets containing antenna performance measurements, simulation results, and design parameters, allowing them to create models that capture the inner relationships among these variables. Researchers can leverage the computational power of ANNs to efficiently explore the design space, identify optimal configurations, and quickly converge on antenna geometries that meet the desired specifications [14].

This study addresses the application of artificial neural networks for the design and optimization of a microstrip antenna adapted for RF energy harvesting circuits operating at 2.4 GHz. Integrating ANNs into the design process not only facilitates the optimization task, but also opens up possibilities for novel antenna geometries that may be difficult to explore with traditional methods. The flow chart of the proposed work is presented in Fig. 1.

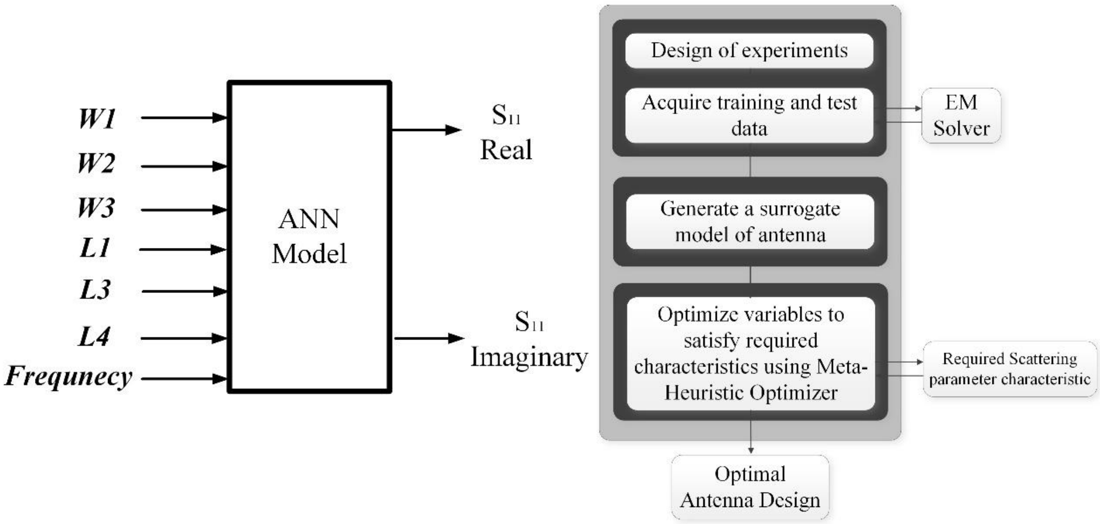


Figure 1. The flow chart of the proposed work

2. Antenna Design and Data Preparation

In this part of the study, a dataset has been prepared according to the variables defined in Table 1 for the microstrip antenna structure presented in Figure 2. According to the ranges provided in Table 1, a different antenna geometry is formed for each variable set. Thus, when the data obtained is presented to the ANN model as training data, the model will establish a relationship between the variables of the antenna geometry and the target output of the problem, which is the return loss (S_{11}). To verify the accuracy of this relationship, an additional dataset (test set) has been prepared. Here, a total of 800 data points have been prepared for training, and 200 data points for testing, with the support of 3D simulators. The frequency range has been set as 0.1-6 GHz. The Latin-Hyper-Cube sampling method has been used as the data sampling technique. In the other part of the study, ANN models related to the antenna have been prepared with the obtained datasets, and an optimization has been conducted with this model to achieve an optimal antenna design for the 2.4 GHz band. The EM simulations are done using CST microwave suit.

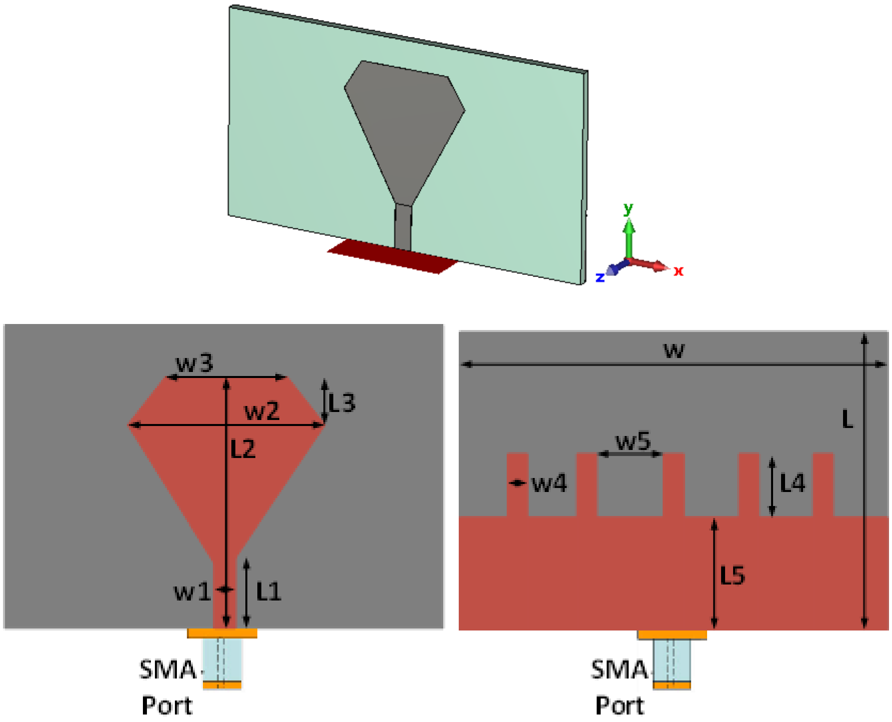


Figure 2. Images of the Proposed Microstrip Antenna

Table 1. *Variable ranges of the proposed microstrip antenna in [mm] (W= 70, L = 40, L5 = 1.5 *L4, W4 = W1, W5 = 4 * W1, L2 = L1 * 4)*

W1	1-5	L1	5-10
W2	15-30	L3	3-10
W3	10-20	L4	3-10

3. Modeling and Simulation Results

The selection of hyperparameters plays a critical role in determining the performance, efficiency, and generalization capabilities of Artificial Neural Networks [15]. Hyperparameters can generally be defined as the number of hidden layers, the number of neurons in each layer, and the type of activation function used. Careful tuning of hyperparameters is crucial to achieve optimal model performance and to overcome specific challenges associated with different tasks [16].

The number of hidden layers in an ANN affects its capacity to capture complex patterns and relationships within the data. As the depth of the network increases, it gains the ability to model complex hierarchical features. However, a deep network can be susceptible to overfitting, especially when dealing with limited data [17]. Adjusting the number of hidden layers to find the right balance is very important to prevent overfitting and allow the network to learn meaningful representations [18].

Activation functions introduce non-linearity to the network, enabling it to learn complex mappings between inputs and outputs. The choice of activation function affects the network's modeling and generalization capabilities [19]. Different activation functions are suitable for different tasks. For instance, the Rectified Linear Unit (ReLU) is known for its simplicity and effectiveness in many scenarios, while in certain cases sigmoid or hyperbolic tangent functions are preferred. The choice depends on the nature of the problem and experimentation is necessary to determine the most suitable activation function.

In this study, experiments were conducted for 1, 2, 3, 4 hidden layers, neuron numbers of 8, 16, 32, 64, 128, and activation functions tanh, sigmoid, and ReLu. To present the results of the study in a more convenient way and easy to understand, the results of the model with the lowest test error from all these experiments have been used. Here more than 100 different models (only 15 different designs for single layer model 5 different neurons size x 3 different activation function) had been tested using Relative Mean Error (RME) Eq. 2 [20]. The targeted value (T) is the S_{11} value provided form the test data set which is a complex number, while the predicted value (P) is provided by the ANN model for each of the test samples over the operation frequency. As it can see from figure 1, the ANN model predict real and imaginary parts of the S_{11} separately and combine them as complex number during the test evaluation. From all these evaluated models, the model with three-layer model with neuron numbers set to 16-32-64 and equipped with the ReLu activation function found to be the optimal design for studied problem. The test performance of the model has been obtained as 4.6% in terms of RME. In a similar approach to the study presented in [21], the ANN model obtained was run with an optimization algorithm aimed at achieving the desired antenna design. The cost function used for this purpose has been presented in equation (2). The design variables obtained at the end of this optimization process are provided in Table 2.

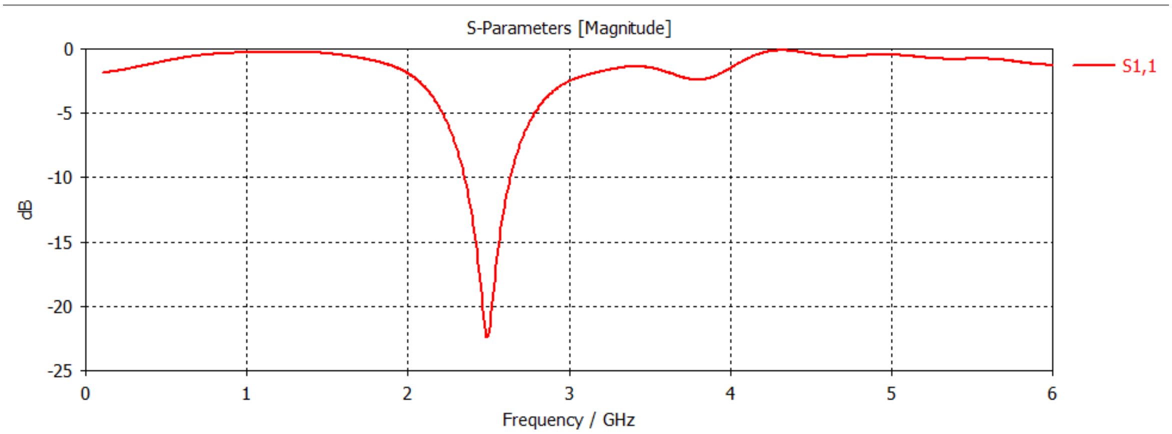
$$RMEt = \frac{1}{n}\sum_{i=1}^{n}\frac{|T_i - P_i|}{|T_i|} \tag{1}$$

$$Cost = \sum_{f_{min}}^{f_{max}}\frac{1}{|S_{11}(f)|} \tag{2}$$

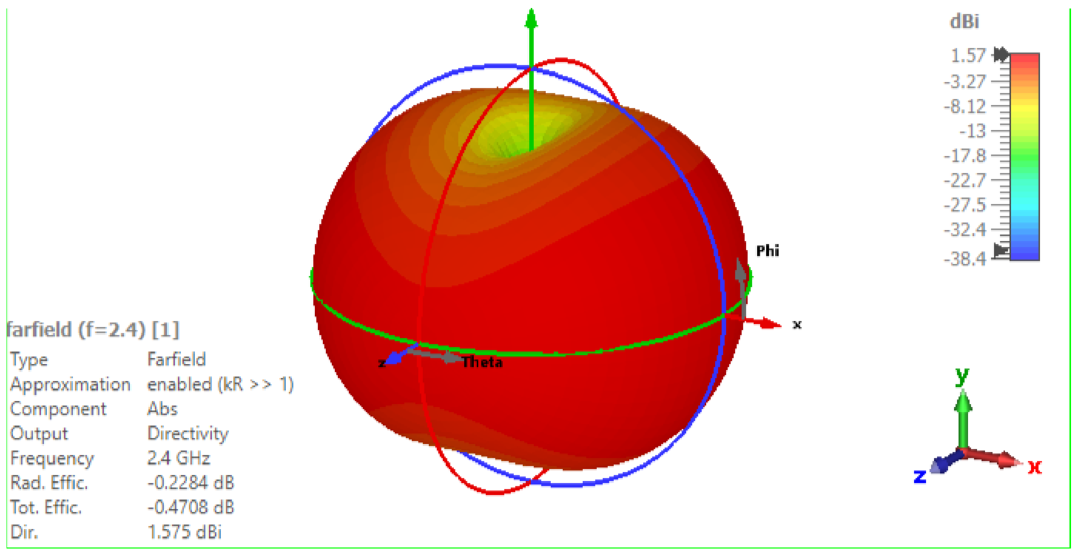
Table 2. *Optimum design variables obtained with ANN-Based optimization in [mm].*

W1	2	L1	8
W2	22.5	L3	5.3
W3	16	L4	8

To verify the accuracy of the obtained optimum antenna design values, the results were inputted into a 3D simulator tool. Figure 3(a) presents the graph of the S_{11} formed based on these data. Figure 3(b) shows the radiation pattern of the antenna at 2.4 GHz.



(a)



(b)

Figure 3. Simulated antenna with optimum variable values showing (a) Return loss S_{11}, (b) 3D radiation pattern

4. Conclusion

In this study, a microstrip antenna design for RF energy harvesting systems at the 2.4 GHz frequency band has been presented using artificial neural networks (ANNs). A 3D electromagnetic (EM) simulation tool was utilized to generate the training and testing data for the ANN model. A series of trial and error iterations and hyperparameters were used to develop the ANN model. These hyperparameters, which are crucial in shaping the learning and optimization capabilities of the neural network, include the number of hidden layers, the number of neurons in each layer, and the type of activation function. The hyperparameter tuning process resulted in the definition of an optimal ANN model. The fine-tuned ANN model through hyperparameter optimization served as a proxy for traditional and time-consuming design processes. This not only accelerated the design phase but also demonstrated the potential of artificial intelligence to efficiently navigate the multidimensional parameter space inherent in antenna optimization. Consequently, the combination of 3D EM simulation tools and artificial neural networks has been proven to be a synergistic and effective approach in the search for optimum microstrip antenna design. This study contributes to the advancement of RF energy harvesting systems by providing a glimpse into the future of computational design methodologies that leverage the power of artificial intelligence to meet the evolving demands of wireless communication and sensor technologies.

Declaration of Interest

The authors declare that there is no conflict of interest.

Author Contributions

Conceptualization, BD MAB; methodology, MAB ; data generation, BD; investigation, BD; designing BD; writing—original draft preparation, BD, MAB; writing—review and editing, MAB; visualization, BD; supervision, MAB; project administration, MAB. All authors reviewed the manuscript.

References

[1] B. Dokmetas, and G.O. Arican, “Design of dual-band SIW antenna for millimeter-wave communication,” 31st Telecommunications Forum (TELFOR), pp. 1-4, November, 2023.

[2] W. A. Khan, R. Raad, F. Tubbal, P. I. Theoharis, and S. Iranmanesh. “RF energy harvesting using rectennas: A comprehensive survey,” IEEE Sensors Journal (2024).

[3] J. Szut, P. Piątek, and M. Pauluk, “RF energy harvesting Energies,” vol. 17, no. 5, 2024.

[4] V. Kuhn, C. Lahuec, F. Seguin and C. Person, “A multi-band stacked RF energy harvester with RF-to-DC efficiency up to 84%,” IEEE Transactions on Microwave Theory and Techniques, vol. 63, no. 5, pp. 1768-1778, May 2015.

[5] X. Zhang, J. Grajal, M. López-Vallejo, E. McVay, and T. Palacios, “Opportunities and challenges of ambient radio-frequency energy harvesting,” Joule, vol. 4, no. 6, pp. 1148-1152, 2020.

[6] P. Mahouti, “Design optimization of a pattern reconfigurable microstrip antenna using differential evolution and 3D EM simulation-based neural network model,” International Journal of RF and Microwave Computer-Aided Engineering, vol. 29, no. 8, 2019.

[7] S. Roshani, S. Koziel, S. I. Yahya, M. A. Chaudhary, Y. Y. Ghadi, S. Roshani, and L. Golunski, “Mutual coupling reduction in antenna arrays using artificial intelligence approach and inverse neural network surrogates,” Sensors, vol. 23, no. 16, 2023.

[8] P. Pragya, and J. S. Sivia, “Design of minkowski curve-based slotted microstrip patch antenna using artificial neural network,” Journal of The Institution of Engineers (India): Series B, vol. 104, no. 1, pp. 129-139, 2023.

[9] M. Mahouti, N. Kuskonmaz, P. Mahouti, M. A. Belen, and M. Palandoken, “Artificial neural network application for novel 3D printed nonuniform ceramic reflectarray antenna,” International journal of numerical modelling: electronic networks, devices and fields, vol. 33, no. 6, 2020.

[10] D. Prabhakar, P. Karunakar, S. V. Rama Rao, and K. Srinivas, “Prediction of microstrip antenna dimension using optimized auto-metric graph neural network,” Intelligent Systems with Applications, vol.21, 2024.

[11] R. Ramasamy and M. A. Bennet, “An efficient antenna parameters estimation using machine learning algorithms,” Progress In Electromagnetics Research C, vol. 130, pp. 169-181, 2023.

[12] S. Koziel, N. Çalık, P. Mahouti and M. A. Belen, “Accurate Modeling of Antenna Structures by Means of Domain Confinement and Pyramidal Deep Neural Networks,” IEEE Transactions on Antennas and Propagation, vol. 70, no. 3, pp. 2174-2188, March 2022.

[13] A. Papathanasopoulos, P. A. Apostolopoulos and Y. Rahmat-Samii, “Optimization assisted by neural network-based machine learning in electromagnetic applications," IEEE Transactions on Antennas and Propagation, vol.72, no.1, pp.160-173, 2023.

[14] S. Koziel, “Fast simulation-driven antenna design using response-feature surrogates,” International Journal of RF and Microwave Computer-Aided Engineering, vol. 25, no. 5, pp. 394-402, 2015.

[15] S. Koziel, N. Çalık, P. Mahouti and M. A. Belen, "Reliable computationally efficient behavioral modeling of microwave passives using deep learning surrogates in confined domains," IEEE Transactions on Microwave Theory and Techniques, vol. 71, no. 3, pp. 956-968, March 2023, doi: 10.1109/TMTT.2022.3218024.

[16] B. Si, Z. Ni, J. Xu, Y. Li, and F. Liu, "Interactive effects of hyperparameter optimization techniques and data characteristics on the performance of machine learning algorithms for building energy metamodeling," Case Studies in Thermal Engineering, 2024.

[17] X. Ying, "An overview of overfitting and its solutions," In Journal of physics: Conference series, vol. 1168, IOP Publishing, 2019.

[18] S. Koziel, N. Çalık, P. Mahouti, and M. A. Belen, "Accurate modeling of antenna structures by means of domain confinement and pyramidal deep neural networks," IEEE Transactions on Antennas and Propagation, vol. 70, no. 3, pp. 2174-2188, 2021.

[19] N. Calik, F. Güneş, S. Koziel, A. Pietrenko-Dabrowska, M. A. Belen, and P. Mahouti, "Deep-learning-based precise characterization of microwave transistors using fully-automated regression surrogates," Scientific Reports, vol. 13, no. 1, 2023.

[20] N. G. Reich, J. Lessler, K. Sakrejda, S. A. Lauer, S. Iamsirithaworn, and D. AT Cummings. "Case study in evaluating time series prediction models using the relative mean absolute error," The American Statistician, vol. 70, no. 3, 2016.

[21] P. Mahouti, A. Belen, O. Tari, M. A. Belen, S. Karahan, and S. Koziel, "Data-driven surrogate-assisted optimization of metamaterial-based filtenna using deep learning," Electronics, vol. 12, no. 7, 2023.