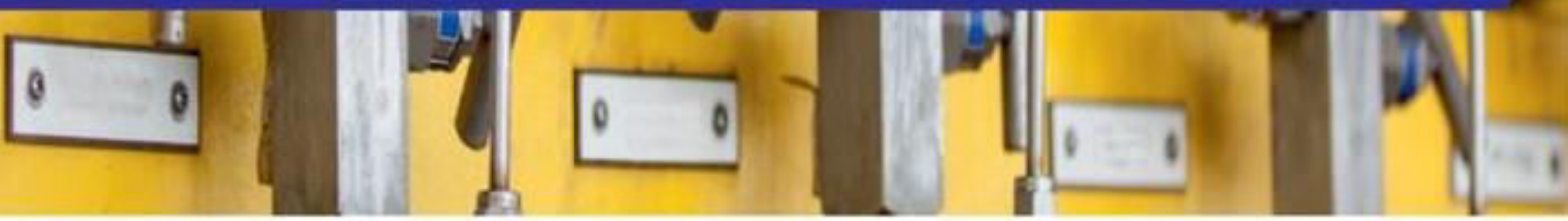
IJAREEIE

e-ISSN: 2278-8875
p-ISSN: 2320-3765

International Journal of Advanced Research

in Electrical, Electronics and Instrumentation Engineering

Volume 15, Issue 8, August 2026



INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 9.867

| e-ISSN: 2278 – 8875, p-ISSN: 2320 – 3765| www.ijareeie.com | Impact Factor: 9.867 | A Monthly Peer Reviewed & Refereed Journal |

|| Volume 15, Issue 8, August 2026 ||

| DOI:10.15662/IJAREEIE.2026.1508006 |

Literature Review on Antenna Design and Optimization using Machine Learning

Niraj R Ada

Assistant Professor, Birla Vishvakarma Mahavidyalaya Engineering College, Vallabh Vidyanagar, Gujarat, India

ABSTRACT: In the recent years the wireless communication has expanded its applications in very broad manner with especially in communication either mobile or internet of things. The increased in the development of the wireless devices has demanded the design and optimizes the antenna which plays a key role in wireless communication. In the conventional methods through which antenna design is time consuming, non-accurate and non-optimistic as per the need of the today's technology. So the machine learning which is evolving domain through different algorithms can be apply to design and develop optimized antenna. The machine learning techniques like, SVM, ANN and GPR antenna parameters can be predicted and improve its design and timing. This paper demonstrate the application of machine learning in antenna design through various methods and provide the approximate optimize design parameters.

KEYWORDS: Antenna, Machine learning, SVM (Support Vector machine), ANN (Artificial Neural Network), GPR (Gaussian Process Regression), MLAO (machine learning assisted optimization)

I. INTRODUCTION

In recent times, industries working with large amount of data have recognized the value of machine learning (ML) technology. Thus, it is widely used in financial services to prevent fraud, in health care to assess a patient's health in real Time, in oil and gas to find new energy sources, in government Services to minimize identity theft, in retail industry to personalize shopping experience, in transportation to make routes more efficient, and many more such applications. However, machine learning has not gained much attention in Computer aided antenna design. With the advent of clever design exploration methods such as space filling Design of Experiments (DOE) approaches, machine learning can be used to speed up the antenna design optimization process tremendously. In addition, machine learning can also accelerate other related simulations such as tolerance studies using stochastic methods.

II. ANTENNA OPTIMIZATION USING MACHINE LEARNING

Machine learning approaches can be applied to any type of antenna design with any number of design variables. The complete workflow of the machine learning approach for antenna design optimization is detailed in the below steps:

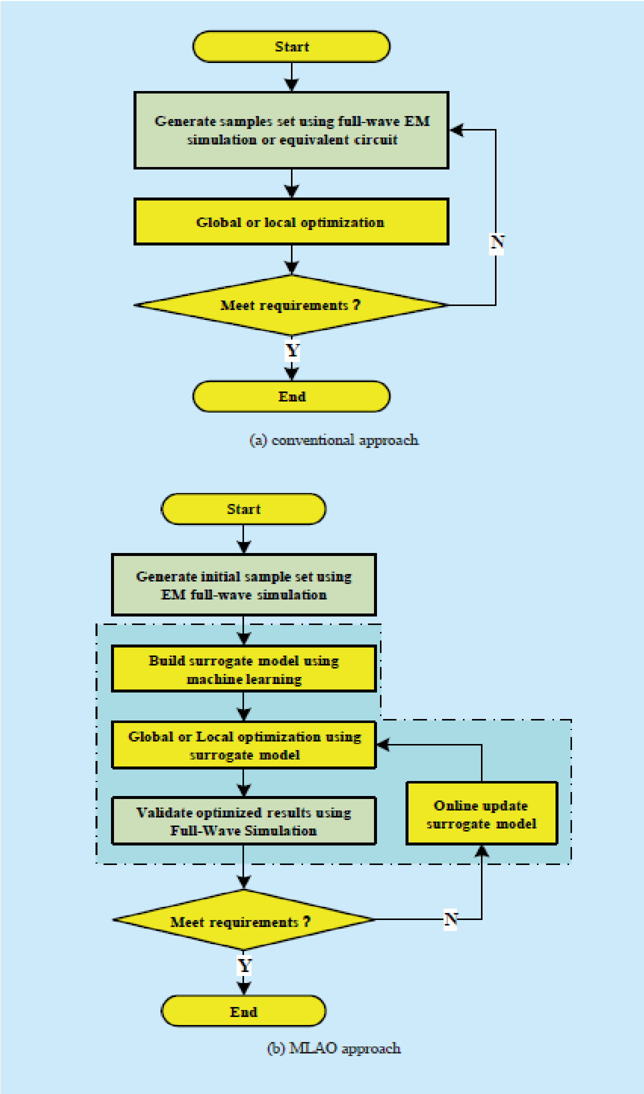
- Generate training and test data with an appropriate DOE
- Study and numerical simulation.
- Build a machine learning model based on the generated
- Training data.
- Validate the machine learning model using the generated test data.
- If the validation is not successful, generate additional training data or use a more appropriate machine learning approach. [1]

How Machine leaning is different than conventional antenna design?

| e-ISSN: 2278 – 8875, p-ISSN: 2320 – 3765| www.ijareeie.com | Impact Factor: 9.867 | A Monthly Peer Reviewed & Refereed Journal |

|| Volume 15, Issue 8, August 2026 ||

| DOI:10.15662/IJAREEIE.2026.1508006 |



(Figure. 1 Machine learning flow Diagram [4])

III. MACHINE-LEARNING-ASSISTED ANTENNA MODELING METHODS

In this section, the most widely adopted ML methods applied in the antenna modeling field are reviewed. In each subsection, the numerical formulations of the method are first introduced, followed by their applications in antenna design.

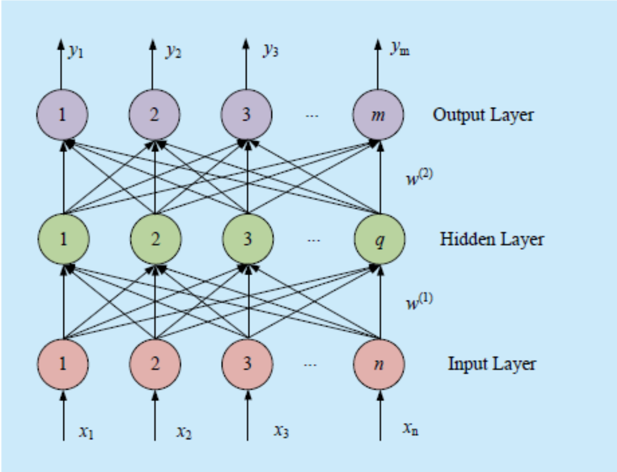
3.1 Artificial neural network

As one of the most well-known ML methods, ANNs were introduced to the electromagnetic field and microwave engineering in 1990s.ANNs have found applications in radar applications, antennas, circuit design, measurement problems, remote sensing, and many other fields. Neural networks are designed to model the way in which the human brain performs a certain task. A general definition of a neural network is given as a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use [5]. An ANN aims to provide an approximation capability for emulating the functions describing the behavior of complex systems based on a non-linear parametric model. The neural network structure consists of two types of basic components: the processing elements, called neurons, and the interconnections, called synapses or links, between them. Each neuron receives stimuli from other connected neurons through links. A typical architecture for an ANN is characterized by an input layer, an output layer and several additional hidden layers to emulate the behavior of $y = M(\mathbf{x})$. A basic architecture for a three-layer ANN is shown in figure 2.[5]

| e-ISSN: 2278 – 8875, p-ISSN: 2320 – 3765| www.ijareeie.com | Impact Factor: 9.867 | A Monthly Peer Reviewed & Refereed Journal |

|| Volume 15, Issue 8, August 2026 ||

| DOI:10.15662/IJAREEIE.2026.1508006 |



(Figure. 2 a three-layer neural network structure with an input layer, a hidden layer and an output layer.)

An ANN was utilized to transform the design parameters, including the dielectric constant and antenna dimensions, and the design objectives, including the antenna's dominant-mode resonant frequency to the patch length. Recently, ANNs with multiple hidden layers, which are usually referred to as Deep Neural Networks (DNNs) or Deep Learning have been introduced to solve antenna parameter and topology optimization problems.[3]

3.2 Support vector machine

The SVM is able to address both classification and regression problems. In a regression problem, the SVM maps the input space into a high-dimensional space named the feature space (H), where the regression can be accurately performed using a linear function. The optimal regression function $\hat{M}(\mathbf{x})$ is considered maximally flat if the training data are properly fitted to a linear function in H, which means that $\hat{M}(\mathbf{x})$ has good generalization properties. The estimation function is given by

$M(\mathbf{x}) = \alpha\phi(\mathbf{x}) + b$

Where α is an unknown normal vector and b is a bias coefficient

SVM requires fewer training patterns to obtain accurate results, which accelerates the training procedure. The SVM has been introduced to model both antenna elements and antenna arrays. The characteristics of microstrip antennas, including the resonant frequency, gain, directivity, radiation efficiency and reflection coefficient, have been efficiently modeled using SVM. [2]

3.3 Gaussian process regression

Recently, the GPR has received extensive attention in the field of EM engineering, including for antenna design. In contrast to the other two ML methods, the GPR is able to provide the uncertainty of the predicted results at new design points, which will help designers to explore global optima when few training points are given [7]. An example of the results and uncertainty predicted by the GPR with 10 sampled points is shown in figure 3. In general, the GPR is a generalization of the Gaussian probability distribution. Whereas a probability distribution describes random variables that are scalars or vectors, a stochastic process governs the properties of functions [7]. A typical single-output GPR (SOGPR) attempts to approximate the target output f (x) by interpreting it as a probability distribution in function space as

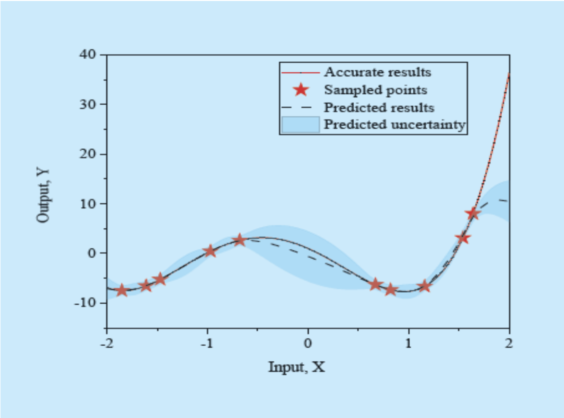
$M(\mathbf{x}) \sim GP(m(x), k(x, x'))$

Where x and x′ are the positions in the design space, m(x) is the mean.[7]

| e-ISSN: 2278 – 8875, p-ISSN: 2320 – 3765| www.ijareeie.com | Impact Factor: 9.867 | A Monthly Peer Reviewed & Refereed Journal |

|| Volume 15, Issue 8, August 2026 ||

| DOI:10.15662/IJAREEIE.2026.1508006 |



(Figure 3. An example of results and uncertainty predicted by GPR with 10 sampled points.)

IV. OPPORTUNITY AND CHALLENGES ON MACHINE LEARNING FOR ANTENNA DESIGN.

MLAO methods have presented a great opportunity to accelerate the optimization process for obtaining practical antenna designs. In the last decade, various types of ML methods for application to different antenna design problems have been investigated. Although ANNs initially became the go-to method to model antennas, SVM and GPR are now more popular due to their highly improved generalization capability, which has proven to be more suitable for practical antenna designs with small data sets. GPR is able to offer the predicted uncertainty at the prediction points, which makes it able to efficiently search unknown areas in the design space and avoid falling into local optima. It can be predicted that more advanced ML methods will be introduced to the antenna design field to produce antenna models with greater generalization capability and accuracy.

One possible direction for accelerating the MLAO process for antenna design is to establish hybrid surrogate models with both data-driven and physical-driven methods. The variable-fidelity MLAO methods can be seen as one such application using hybrid models, which utilize both physical-based and data-based information to predict responses at new points. With the development of modern communication systems, the SA and robust design are becoming indispensable in the antenna design process and requires more function calls than naïve antenna optimization problems [4].

MLAO is able to accelerate the SA process for antenna design but is still very time consuming for complex antenna structures with large numbers of design parameters and large design ranges. The MLAO method for antenna SA is a promising research direction and will be very useful in practical communication system designs.[4] The rapid analysis of large-scale antenna arrays remains an unsolved problem. Considering the longer full-wave analysis process of antenna arrays compared with antenna elements, improved techniques are necessary for both optimization and SA analysis problems of large-scale antenna arrays.

Although Machine Learning is very useful, it comes with a lot of challenges. The most common challenges include but are not limited to:

1) The choice of learning algorithm: It is not easy to decide what algorithm to choose as there are a great number of them. This depends directly on what is being predicted and also on the type of data acquired. A good practice is to always visualize the data before choosing the algorithm [5].

2) Problem Formulation: Beginning with wrong assumptions usually lead to worthless results that can cost a lot of time. It is necessary to know what area of the problem is best to spend time working on.

3) Getting enough data: Some data can be hard to find or obtain. In antenna design, multiple simulations are needed in order to obtain a training set.

4) Pre-processing of data: To ensure that the learning algorithm performs adequately, multiple steps need to be performed on the data, such as data cleaning, normalization and feature selection, which would cost time in case of very large datasets.

5) Debugging the algorithm: Knowing what to do next can also be challenging. When problems, such as high bias and high variance occur, it is crucial to know what steps to take. This requires following some diagnosis techniques such as plotting the learning curves.

| e-ISSN: 2278 – 8875, p-ISSN: 2320 – 3765| www.ijareeie.com | Impact Factor: 9.867 | A Monthly Peer Reviewed & Refereed Journal |

|| Volume 15, Issue 8, August 2026 ||

| DOI:10.15662/IJAREEIE.2026.1508006 |

V. CONCLUSION

A comprehensive survey of MLAO algorithms for antenna design was presented. First, three popular ML methods in the antenna modeling field were introduced along with their fundamental formulations and applications in antenna modeling. Then, various algorithms utilizing ML methods for antenna problems were reviewed, therein focusing on different applications using different techniques. Finally, some instructions for the future development of MLAO for antenna design were given. While great improvements in antenna optimization and SA have been observed after introducing MLAO methods, many challenges remain for future investigation.

REFERENCES

[1] Y. Sharma, H. H. Zhang, and H. Xin, "Machine Learning Techniques for Optimizing Design of Double T-Shaped Monopole Antenna," IEEE Trans. Antennas Propag., vol. 68, no. 7, pp. 5658–5663, Jul. 2020, doi: 10.1109/TAP.2020.2966051.

[2] D. R. Prado, J. A. Lopez-Fernandez, M. Arrebola, M. R. Pino, and G. Goussetis, "Wideband Shaped-Beam Reflectarray Design Using Support Vector Regression Analysis," IEEE Antennas Wirel. Propag. Lett., vol. 18, no. 11, pp. 2287–2291, Nov. 2019, doi: 10.1109/LAWP.2019.2932902.

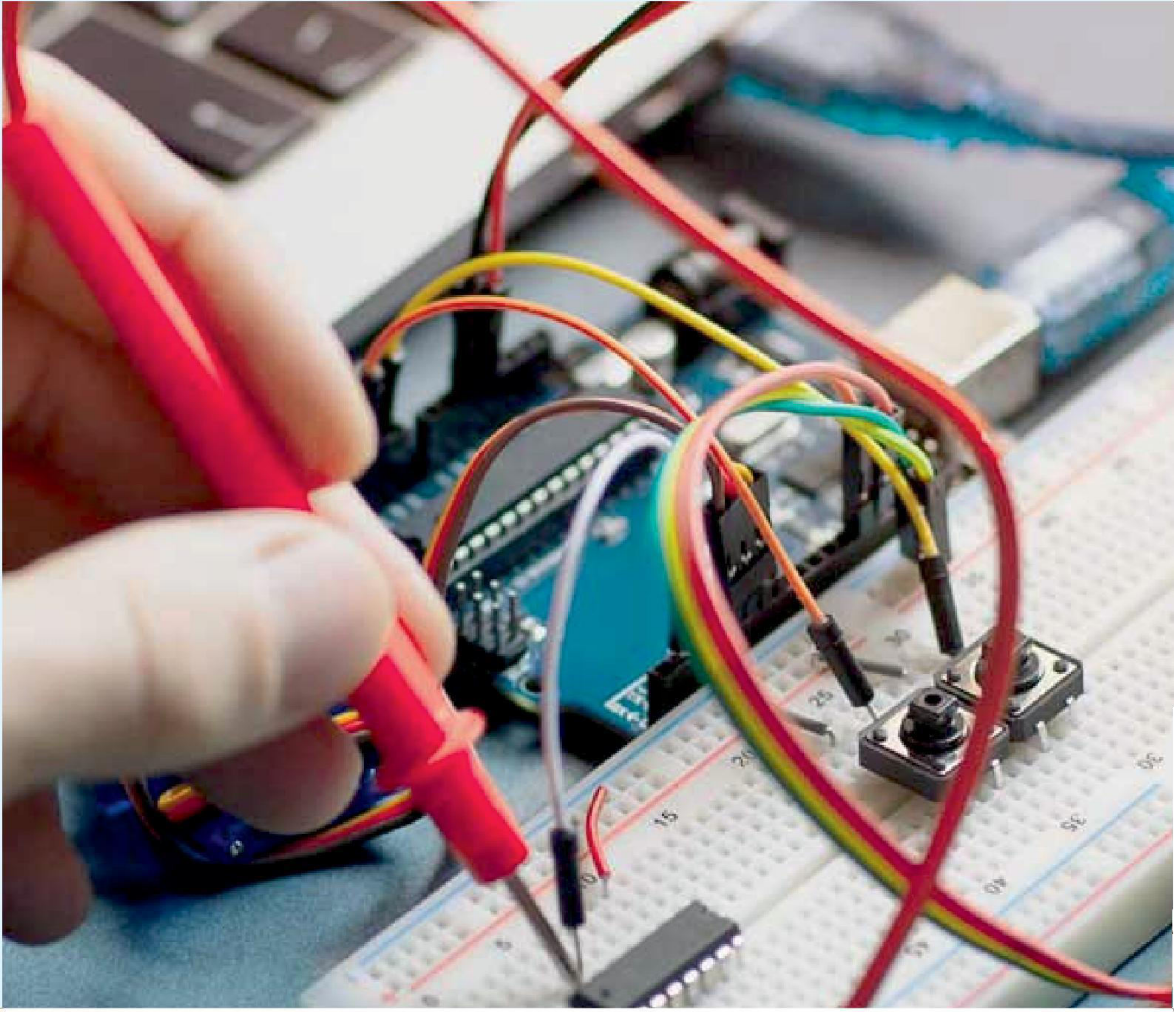
[3] Q. Wu, H. Wang, and W. Hong, "Multistage Collaborative Machine Learning and its Application to Antenna Modeling and Optimization," IEEE Trans. Antennas Propag., vol. 68, no. 5, pp. 3397–3409, May 2020, doi: 10.1109/TAP.2019.2963570.

[4] Q. Wu, Y. Cao, H. Wang, and W. Hong, "Machine-learning-assisted optimization and its application to antenna designs: Opportunities and challenges," China Commun., vol. 17, no. 4, pp. 152–164, Apr. 2020, doi: 10.23919/JCC.2020.04.014.

[5] H. M. El Misilmani, T. Naous, and S. K. Al Khatib, "A review on the design and optimization of antennas using machine learning algorithms and techniques," Int. J. RF Microw. Comput.-Aided Eng., vol. 30, no. 10, Oct. 2020, doi: 10.1002/mmce.22356.

[6] Q. Wu, J. Yin, C. Yu, H. Wang, and W. Hong, "Machine-Learning-Assisted Two-Step Antenna Modelling Method," in 2019 IEEE International Symposium on Antennas and Propagation and USNC-URSI Radio Science Meeting, Atlanta, GA, USA, Jul. 2019, pp. 1043–1044, doi: 10.1109/APUSNCURSINRSM.2019.8889236.

[7] S. Koziel and J. P. Jacobs, "Gaussian process antenna modeling using neighborhood-data-expanded training sets," in 2013 IEEE Antennas and Propagation Society International Symposium (APSURSI), Orlando, FL, USA, Jul. 2013, pp. 1282–1283, doi: 10.1109/APS.2013.6711301.



International Journal of Advanced Research

in Electrical, Electronics and Instrumentation Engineering

9940 572 462 6381 907 438 ijareeie@gmail.com

Scan to save the contact details

www.ijareeie.com