Design of Antenna Parameters Using Optimization Techniques: A Review

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Abstract

The use of machine learning (ML) and deep learning (DL) algorithms to solve mathematical issues in wireless communications has propelled AI-assisted communications to the forefront in recent years. Beginning with an overview of AI, CEM, and the function of AI/ML/DL in antennas, this paper moves on to discuss the topic in more depth. In this article, we show the results of our research into ML/DL algorithms and the methods we used to optimize antenna settings using these algorithms. Finally, we show several examples of how AI can be used in antennas.

Keywords: Artificial Intelligence; Antenna Optimization technique; Deep learning; Machine learning.

1. Introduction

By modelling human cognition and behaviour, artificial intelligence (AI) enables the creation of smart devices. There have been a lot of theoretical advances in AI communications, but not a lot of actual hardware developments. Computer science includes the subfields of AI, ML, and DL. These are the cutting-edge methods now being used to develop sophisticated computer programmes. Machine learning (ML) is a branch of artificial intelligence that allows machines to learn from data without being explicitly programmed. Multi-layered neural networks are made accessible to examples in DL, a subtype of ML. Supervised DL, semi-supervised DL, unsupervised DL, and reinforced DL are the subcategories of DL based on the use of neural networks.

Machine learning (ML) algorithms allow for AI to function via ANNs. The availability, quantity, and quality of data are crucial to the success of ML. This information will be gathered by simulating the desired antenna using CEM simulation software tools, given a certain antenna design. A dataset is built upon the findings. This dataset has the added benefit of being divisible into training, cross-validation, and testing sets. A machine learning model is trained and tested using these datasets. The connection among AI, ML, and DL is illustrated in Figure 1.

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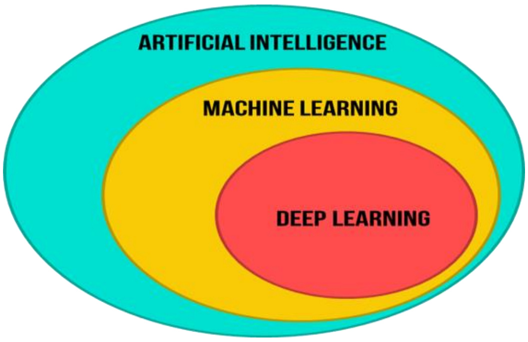

Figure 1: Relation between AI, ML, and DL

2. Related Work

The first ANN computational model was presented by McCulloch and Pitts in 1943. Academic interest in artificial intelligence (AI) increased after its introduction in 1956. The 1970s were known as "AI winter" because of a lack of investment. In the mid-1980s, AI made strides thanks to updated ANNs and backpropagation [1]. Applications such as recognising handwritten signatures on checks ensured its continuation into the 1990s and the 2000s. Deep neural networks (DNNs) were responsible for the subsequent progress.

Training deep neural networks (DNNs) using NVIDIA graphics processing units (GPUs) in 2009 marked the "big bang" of DL. The DL upheaval then started in 2012. In the years after 2015, convolutional neural networks (CNNs) prevailed by surpassing a human-targeted benchmark. The fact that CNNs can categorise images more accurately than humans is a huge step forward in artificial intelligence. In 2016, a DNN-based system called AlphaGo won a Go championship against human opponents. To put it another way, "democratisation of AI" has occurred since then. Companies that rely on cloud computing technology now use DL to enhance their offerings.

A. Computational Electromagnetics

Maxwell's equations are used in Computational Electromagnetics (CEM) to describe how EM fields interact with antennas. At first, linear antennas were solved using integral equations. Later, with the advent of computers, both differential and integral solvers made quick work of Maxwell's equations. Then, to resolve integral equations, the Method of Moments (MoM) was presented. The primary drawbacks of differential and integral solvers are their high memory and CPU demands. The iterative fast integral solvers [2] were developed to meet the decreased memory requirements. The various CEM approaches are depicted in Figure 2.

Numerical methods and high-frequency methods are CEM techniques used in antenna design. Finite difference time domain (FDTD), the method of moments (MoM), and the finite element method (FEM) are common numerical methods used in antenna simulations and testing. The radiation fields of a high-frequency reflector antenna are calculated using the physical optics (PO) approach. Partial differential equation (PDE) solving with boundary conditions is required for antenna simulations. Field-based Geometric Optics (GO) and current-based PO are two high-frequency techniques. The multiple multipole program (MMP), the generalised multipole method (GTM), the transmission line matrix method (TLM), and the conjugate gradient method (CGM) are some other examples of such approaches. HFSS, CST, ADS, and IE3D are the commercial CEM software tools. The execution time of CST and HFSS is longer and is related to the size of the antenna; ADS does not model the 3D shapes; and IE3D is unable to simulate structures with limited features; these are just a few of the limitations of these tools.

B. AI in Antennas

Communications systems need to be able to reconfigure and adapt to survive in the hostile and crowded radio spectrum. Artificial intelligence is commonly used in reconfigurable and adaptive antenna arrays. Altering the current distribution across the aperture of a reconfigurable array can change its polarisation, radiation pattern, and operating frequency. Instantaneously [3,] the Adaptive arrays mix and weigh signals to boost the intended signal while suppressing interference. It employs software beamforming techniques and alters antenna layouts by adjusting the element weights. Faster and more accurate strategies for determining element weights have recently been implemented in AI

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algorithms. When compared to conventional signal processing techniques, AI excels in complex, noisy, and multipath settings. Signals are managed using digital beamforming techniques, which in turn depend on the array's architecture.

C. ML Algorithms

Specifically for the optimisation of designs with huge shapes and more parameters, ML in the antennas field greatly decreases the significant processing times of CEM techniques. By utilising high-performance computers, ANNs are able to simulate EM structures with minimal computational resources, a small error margin, and a short training time. In the field of antenna research, DL is commonly employed to solve problems involving remote sensing and inverse scattering (IS) [1]. IS requires few receiving antennas to determine the form of a scattering structure. Deep NIS is a convolutional neural network (CNN) for nonlinear EM IS that requires fewer receiving antennas.

3. Machine Learning Algorithms

For better decision-making, ML employs statistics, data searching, interpolation, and optimisation [3]. ML algorithms as seen in figure 2 are:

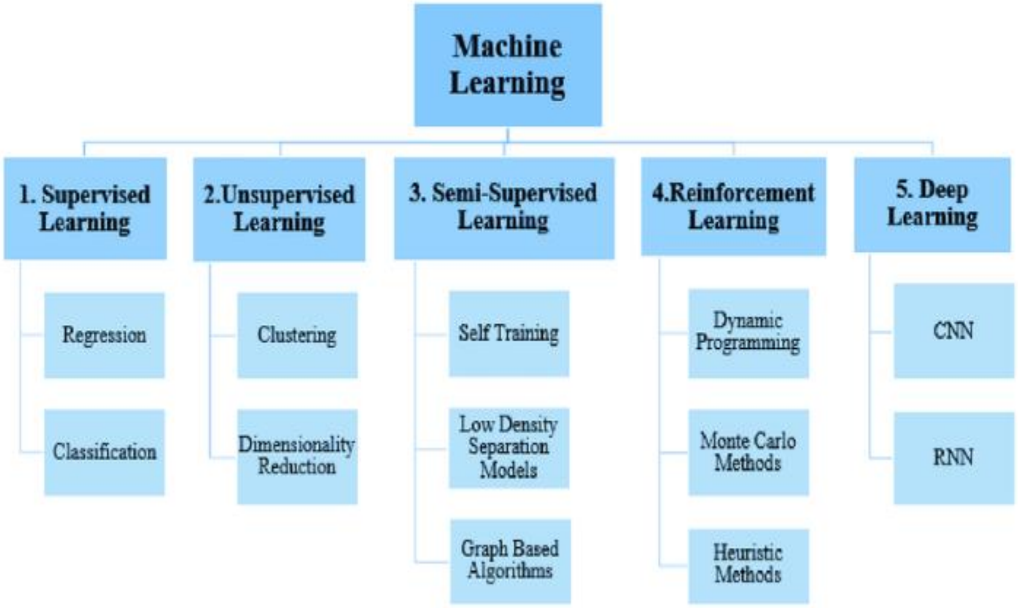

Figure 2 : Machine learning classification

A. Machine learning categorizes

ML converts mathematical optimisation issues to data-driven challenges of lower computer complexity. There are three broad groups of ML [4, 5]. They do,

1- Supervised learning

This learning assignment makes predictions on unseen input using labelled input-output pairs. Targets or labels are related with training data, but they are absent in testing data. The following are the subcategories of supervised learning:

1.1 Regression

Unseen data labels are predicted from available data in this manner. Least absolute shrinkage and selection operator (LASSO), linear regression (LR), kernel ridge regression (KRR), and support vector regression (SVR) are regression algorithms.

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1.2 Classification

This technique labels data from a limited number of classes. This method combines both binary and multi-class categorization.

2- Unsupervised learning

Based on the unlabeled datasets, this approach predicts labels for fresh data. There is no distinction between training and testing data in this case. Unsupervised learning is classified further as follows.

2.1 Clustering

For huge datasets, clustering is utilized. It locates regions or clusters of data inside the datasets.

2.2 Dimensionality reduction

It is also known as manifold learning. The dimensions of the data are lowered here without affecting the primary characteristics of the initial data.

3- Reinforcement learning

In this case, the learner is an agent who actively interacts with the learning environment in order to achieve a common goal. Optimization, cognitive sciences, and control theory all employ this paradigm. In this sector, Markov decision processes (MDPs) are commonly used. Figure 3 depicts many forms of ML.

B. Artificial and deep neural networks

FEM employs ANNs in addition to typical CEM approaches to minimize the energy function. Because of its stability, ANNs are also used by MoM. ANNs are used in distributed computing to handle difficult EM issues. ANNs were also utilized to accelerate FDTD. Neural Networks, often known as ANNs, are supposed to behave similarly to the human brain. It is made up of several perceptron.

1- Perceptron

Input and output are provided by the artificial neuron or node. The mathematical function represents it. A biological neuron in ANN is commonly referred to as a perceptron. A single-layer neural network is used. Figure 3 depicts a perceptron model. Perceptron is mathematically represented as follows:

$$y = \sum_{i=1}^{n} w_i x_i \tag{1}$$

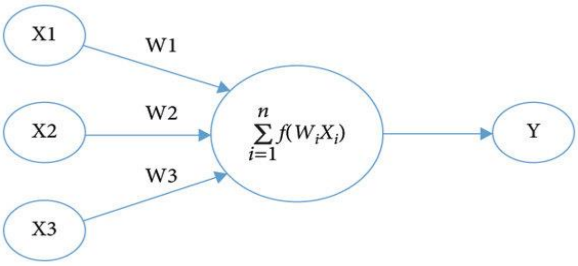

Figure 3: Perceptron model

2- ANNs

Because it learns and improves the property, the information that goes through the system has an effect on the planned ANN. Figure 4 depicts the many forms of ANNs. The input, hidden, and output layers comprise the three layers of ANN. The structure of ANN and DNN is depicted in figure 5.

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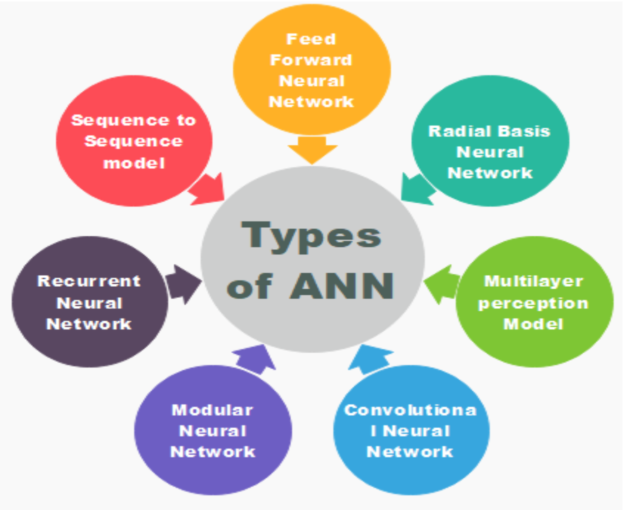

Figure 4 : ANNs Types

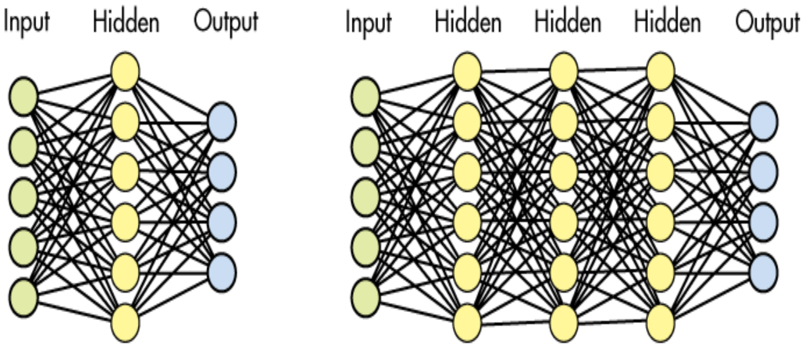

Figure 5: Structure of ANN (single layer) and DNN (multilayer)

3- DNNs

DNNs are members of the ANN family. It is made up of three or more hidden layers [7].

C. Machine learning framework

The ML frameworks were based on optimized code written in Java, R, Python, and other languages, allowing for quick and flexible use of multiple techniques [4]. The following are some of the frameworks.

1- Regression models with learning algorithms

These techniques [7] aided in the development of the nonlinear link between geometrical parameters and antenna properties. ANN, SVR, Gaussian Process Regression (GPR), LASSO, LR, Broad learning system (BLS), and KRR are typical ML techniques used in antenna design.

2-Training ML models with optimization algorithms

The bias parameters and appropriate weight for the ML model are determined using optimization methods. They are used in the ML model training process to discover the optimal parameter values and to minimize the cost function. The antenna design optimizers are as follows.

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1) **Gradient descent (GD)**
The GD algorithm/batch is sluggish since it updates the parameters after evaluating the gradient of the entire dataset. GD is stuck in local minima on a non-convex surface before converging to the global minimum. As an alternative, stochastic gradient descent (SGD) can be used.

2) **Adaptive moment estimation (ADAM)**
Because it updates the parameters after analyzing the gradient of the entire dataset, the GD algorithm/batch is slow. Before converging to the global minimum, GD is locked in local minima on a non-convex surface. Stochastic gradient descent (SGD) can also be utilized as an alternative.

3) **Levenberg Marquardt (LM) algorithm**
LM is used to solve nonlinear least-squares estimation issues with a function's local minimum. It is a batch trust-region optimization method. It is faster than vanilla GD since it mixes GD and Gauss-Newton iterations.

4) **Bayesian regularization (BR)**
Instead of error backpropagation, BR trains ANNs through extensive cross-validations. Overtraining and overfitting Bayesian regularized ANNs are problematic.

5) **Evolutionary algorithms**
These are employed in global optimization and are inspired by the evolutionary process and the behavior of live beings. They are employed in electromagnetic optimization and include GAs, differential evolution (DE), particle swarm optimization (PSO), and others.

3- Predicting antenna parameters with ML models

Simulations are used to build the database at first. The dataset is then divided into training, cross-validation, and test sets. To learn from the data, an ML algorithm is chosen. After training and testing the model, the output values for desired inputs are predicted. Predictions are made at rapid speeds with small margins of error. The metrics used to quantify errors are as follows:

- **Output error**
  It is the discrepancy between the output of simulations and the output of the ML model's predictions. It is written as

$$e_o = y_d - y_p$$

Where,
e_o: error in output
y_d: desired Output
y_p: Expected output

- **Mean square error (MSE)**

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(e_0)^2$$

Where, N= training sample size

The percentage of error is

$$error\ \% = |\frac{y_d - y_p}{y_d}| \times 100$$

4. Design and optimization of antennas using ML/DL algorithms

Using multi-layer perceptron (MLP) and RBF, the dimensions of the rectangular microstrip patch antenna (RMPA) are calculated using the resonance frequency (f_r), permittivity, and height of the substrate as input parameters. SVR was used to optimize the operational bandwidth, input impedance, and f_r of the RMPA [9]. Table 1 shows how researchers utilized various ML algorithms to construct antennas.

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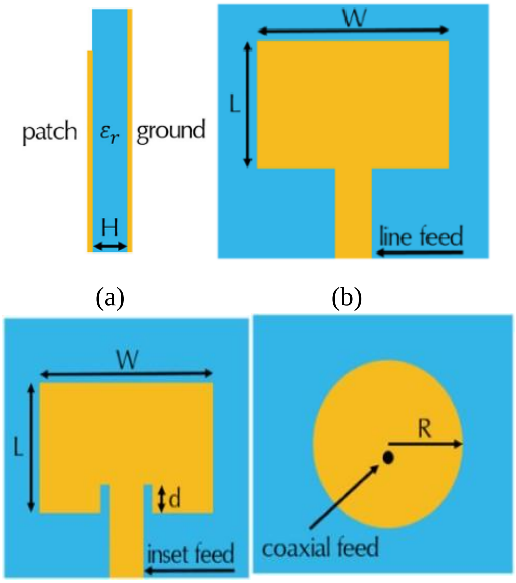
Table 1: shows the reported antennas that used ML algorithms

work	Type	Algorithm
[8,12]	RMPA	ANN
[9,10]	RMPA	SVR
[11]	RMPA	SVR, ANN
[13-15]	CMPA	ANN
[16]	Monopole	ANN
[17]	Two Slot RMPA	ANN
[18]	SIW	GPR
[19,20]	Reflector array	Kriging Regression

In [10], gain, f_r, and VSWR were calculated using SVR with a Gaussian Kernel and the length and breadth of RMPA. SVR and ANN models were used in [11] to estimate slot size and position. The robust backpropagation (RPROP) algorithm, feed-forward backpropagation (FFBP) algorithm, RBF algorithm, and LM algorithm were used to build a printed antenna in [12]. MATLAB was used to train and test them. In this case, input characteristics such as patch size, dielectric constant, and substrate thickness are used to predict output parameters such as antenna f_r. An MLP model was used in [13] to predict the radius 'a', directivity, and feed position of a circular microstrip patch antenna (CMPA). The f_r of CMPA was predicted in [14, 15] using the patch thickness, radius, and dielectric constant of the substrate.

Figure 6 depicts the RMPA and CMPA structures. [16] achieved the feed gap of a circular monopole antenna to operate within a specific frequency range modelled by ANN. [17] used RBF and MLP-based ANN models to create a two-slot RMPA. The GPR technique was used to create a broadband mm-wave substrate integrated waveguide (SIW) cavity-backed slot antenna in [18]. Kriging Regression was applied for reflector array antennas in [19, 20].



(a) (b)

(c) (d)

Figure 6: (a), (b), (c), (d) Rectangular and circular patches with different feeds

On the other hand, several researchers worked on embedding ML models into optimization methods to increase antenna performance, resulting in reduced simulation time. A comparison of antennas is shown, as well as the optimization and ML strategies employed in table 2.

Table 2: Reported antennas with both optimization and ML algorithms

work	Type	Optimization algorithm	ML algorithm
[21,22]	Slot	Space mapping	BSVR

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[23,24]	Ring monopole	GA	Interpolation
[25]	Inter chip	SMA-DE	GPR
[26]	E shaped	DE	Kriging
[27-30]	Stacked patch	PSO	ANN

5. Applications of AI in Antenna

MIMO antenna selection for diversity [31], Reconfigurable intelligent surfaces [32, 33], wireless localization, adaptive nulling, beamforming topologies, calibration, element failures, and multi-input and multi-output (MIMO) applications are examples of AI applications in antennas. These are briefly covered below.

A. Wireless localization

Wireless localization investigates the positions of desired targets for navigation and tracking. CNNs and SVMs are the most often used AI approaches for active localization, in which the target holds a gadget that sends some kind of signal. The target does not hold the device in a device-free localization.

B. Adaptive nullification

Adaptive nulling in a cylindrical array recognises nulls in the pattern by utilising the least significant bits of the element weights while minimising total output power. To maximise the signal to interference ratio (SIR), an ML algorithm and DBF architecture are required. This approach not only lowers the cost function, but it is also useful in multipath and noisy settings. Adaptive nulling employs beamforming in conjunction with a network of software-defined radios (SDRs) and Gas [34].

C. Beamforming

For typical beamforming, an active electronic scanning array (AESA) with an N-element is ideal. It scans the main beam and decreases sidelobe levels. This technology limits the reconfigurable and adaptive functionalities and has inferior resolution over the digital beamforming (DBF) architecture, which replaces software beamforming in the computer with RF beamforming. SDRs are now often employed in DBFs. This SDR performs cognitive sensing of its surroundings as well as adaptive nulling. figures 7 and figure 8 depict the SDR beamformer and its setup.

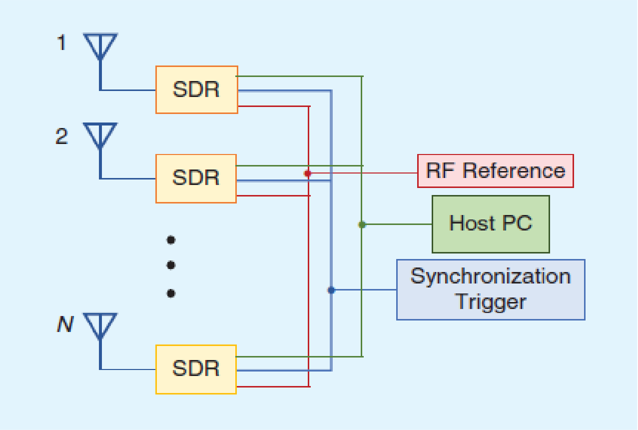

Figure 7: Block diagram of an SDR beamformer [34]

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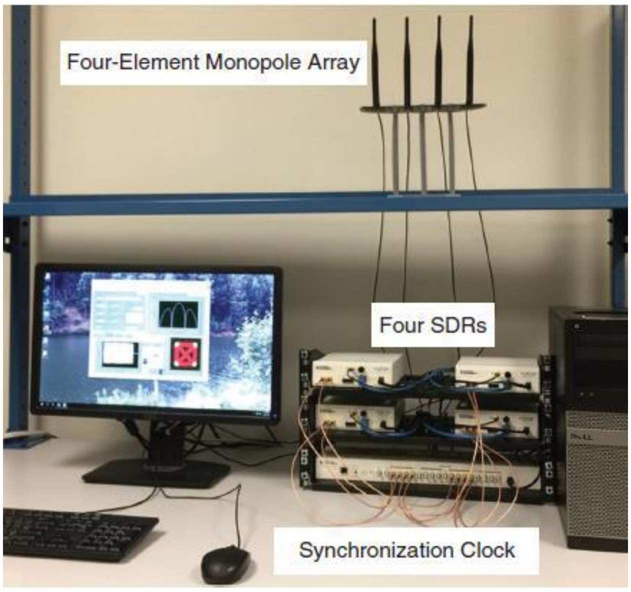

Figure 8: The setup of the 4-element SDR beamformer [34]

D. Communication using MIMO

MIMO improves a system's overall capacity. MIMO with DL algorithms will make use of CAP MIMO transceivers and channel state information (CSI) estimates [35]. In MIMO smart antenna arrays, AI finds applications for analogue, hybrid, and digital beamforming. A situational awareness strategy is integrated with machine learning techniques to learn information about the beam from past observations and subsequently rearrange the antenna array for mm-wave vehicular applications. Figure 9 depicts the CAP MIMO antenna's architecture.

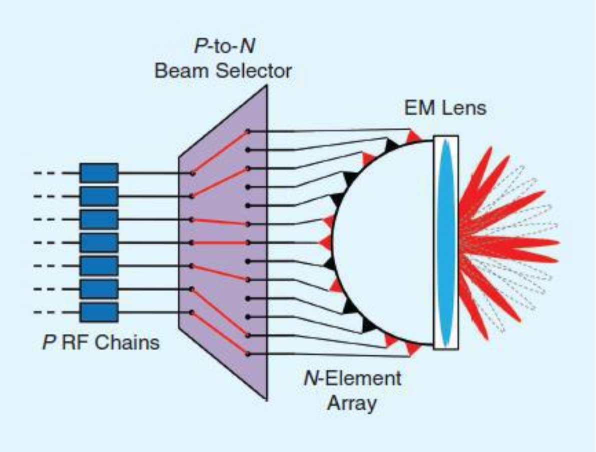

Figure 9: The architecture of CAP MIMO antenna [35]

E. Failure of an element

It is a performance deterioration, not a system breakdown. The degraded performance is compensated for by altering the array beamforming network. The faulty pieces are first detected here. SVM, GAs, NN, and case-based reasoning (CBR) are some of the AI methods proposed for this job. Even if one element fails, the radiation pattern of a tested antenna is the same as the reference one [36]. Figure 10 depicts the radiation properties of a GA optimized array.

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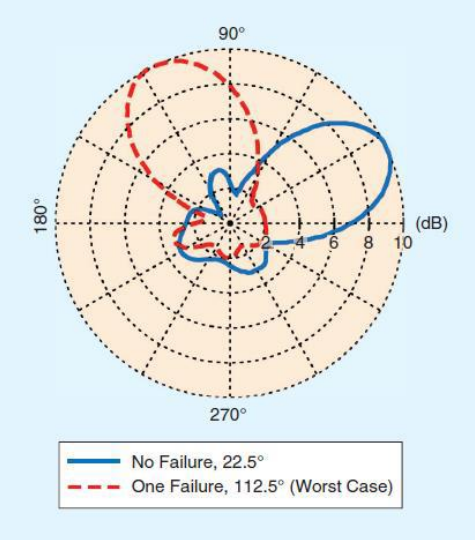

Figure 10: Radiation characteristics of GA optimized array [36]

F. Calibration of Arrays

Calibration is essential in antenna arrays for the hardware to avoid pattern variations. Massive MIMO can use the same channel for uplink and downlink thanks to time division duplexing. Reciprocity exists in both directions for the channel transfer function between the transmitter and receiver [39-41]. Variations in the phase and amplitude of RF chains will disrupt the reciprocity of two communicating devices in practice, however customized ANNs will overcome this issue. In a testing arrangement, a base station emulator connects with ports for each antenna to the device under test (DUT) through physical wires. In a wireless technique, test signals are first sent over the air to the required antenna port, and then the transfer matrix (H) between the DUT and testing equipment is compensated for [37]. The PSO offers a scaled solution for a large number of antennas. Figure 11 depicts a GA-based array calibration system.

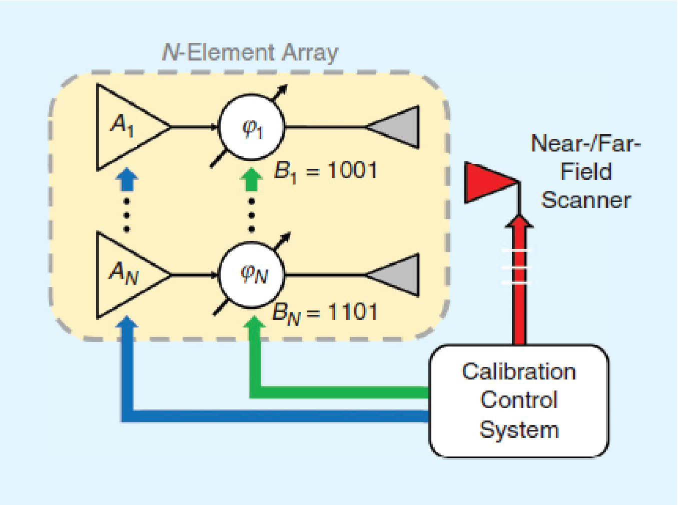

Figure 11: GA based system for array calibration [37]

6. Conclusion

AI has a wide range of applications in antennas. AI makes a substantial contribution by tackling nonlinear and huge problems with various variables. Adapting to noisy and multipath settings is

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beneficial. Over classic CEM techniques, it is believed that ANNs and DNNs have played a significant role in the research domain of ML/DL techniques. In complicated antenna design CEM tools, an ML/DL method enhances performance attributes while decreasing calculation time. In addition, this study discusses the role of AI/ML/DL in antenna design and analysis [42-43]. A comparison of numerous research articles that used ML/DL algorithms for design and optimization is also offered [44-48].

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