A Review on Optimization Techniques of Antennas Using AI and ML / DL Algorithms

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Abstract. In recent years, artificial intelligence (AI) aided communications grabbed huge attention by providing solutions for mathematical problems in wireless communications by using machine learning (ML) and deep learning (DL) algorithms. This paper initially presents a brief background on AI, CEM, and the role of AI/ML/DL in antennas. A study on ML/DL algorithms and the optimization techniques of antenna parameters using various ML/DL algorithms are presented. Finally, the application areas of AI in antennas are illustrated.

Keywords: Artificial intelligence, Antenna optimization techniques, Computational Electromagnetics, Deep learning, Machine learning, ML/DL algorithms, Neural networks

1. Introduction

Artificial intelligence (AI) creates intelligent machines that simulate human thinking capability and behavior. Many advancements in AI communications stay at a theoretical level, and few of them are in hardware implementation. AI, ML and DL are the parts of computer science. These are the most trending technologies now a days to create intelligent systems. ML permits machines to learn from the data without precise programming, and it is the subset of AI. DL is the subset of ML which exposes multilayered neural networks to example data. DL is classified based on neural network usage as supervised, semi-supervised, unsupervised, or reinforcement.

ML algorithms enable AI by artificial neural networks (ANNs). The ML success depends on the data's availability, quantity, and quality. Given antenna design, this data will be obtained by simulating the desired antenna on CEM simulation software tools. Then from the results, a dataset is created. Further, this dataset can be divided into three sets training, cross-validation, and testing. These sets are used to train and validate an ML model. Figure 1 shows the relation between AI, ML, and DL.

2. Background

McCulloch and Pitts in 1943 introduced the first computational model of ANN. AI was introduced into academics in 1956 and saw progress in interest in the 1960s. In the 1970s, it was "AI winter" due to a lack of funding. AI progressed in the mid-1980s due to renewed ANNs and backpropagation [1]. Further, it continued in the 1990s and 2000s due to applications like handwritten check signature detection. Further advancements were due to deep neural networks (DNNs).

The “big bang” of DL took place in 2009 as NVIDIA GPUs are used to train DNNs for the first time. Then in 2012, the DL revolution began. After 2015, convolutional neural networks (CNNs) stood first by breaking the benchmark targeted by human experts. It is a remarkable advancement in AI as CNNs are better than humans in labeling images. In 2016 AlphaGo system based on DNN beat a human Go championship. Since then, the "democratization of AI" has taken place. Now cloud computing technology-based companies use DL to improve their products and services.

2.1. Computational Electromagnetics

Computational Electromagnetics (CEM) is used to characterize the interaction of electromagnetic (EM) fields with antennas using Maxwell's equations. Initially, integral equations were used to solve linear antennas. Later on, due to the developments of computers, solving Maxwell's equations by both differential and integral solvers became easy. Then, the Method of Moments (MoM) was introduced to solve integral equations. Generally, memory and CPU usages are the main drawbacks for the differential and integral solvers.

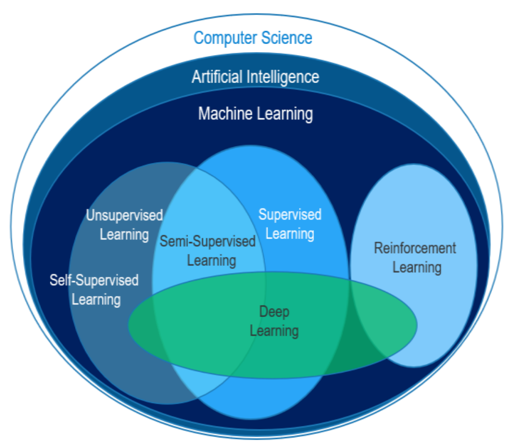

Fig. 1 Relationship between AI, ML, and DL

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To fulfill the reduced memory demands, the fast integral solvers were implemented, which involved iterative methods [2]. Figure 2 shows the types of CEM methods.

CEM methods in antenna design are numerical methods and high-frequency methods. The popular numerical methods in antenna simulations and testing are finite difference time domain (FDTD), MoM, and finite element method (FEM). By the physical optics (PO) method, the radiation fields of high-frequency reflector antenna are obtained. Antenna simulations need solving partial differential equations (PDE), considering boundary conditions. High-frequency methods are field-based Geometric optics (GO) and current-based PO. Other methods are the multiple multipole program (MMP), generalized multipole technique (GTM), transmission line matrix method (TLM), and conjugate gradient method (CGM). The commercial CEM software tools are HFSS, CST, ADS, and IE3D. A few drawbacks of these tools are the execution time of CST and HFSS is more, and it is proportional to the size of the antenna, ADS does not model the 3D shapes, and IE3D cannot simulate shapes with finite details.

2.2. Role of AI in antennas

The hostile and crowded radio spectrum requires communications systems that reconfigure and adapt to the environment. Particularly reconfigurable and adaptive antenna arrays widely use AI. To change reconfigurable array polarization, radiation pattern, and operating frequency, the current distribution is altered across the aperture. The Adaptive arrays instantaneously weigh and combine signals to enhance the desired signal and reject interfering signals [3]. It changes antenna patterns by tuning the element weights and uses software beamforming algorithms. Recently, AI algorithms have upgraded with fast and superior methods to find element weights.

AI is better than traditional signal processing algorithms in noisy and multipath environments. AI depends on the architecture of the array and it controls signals by digital beamforming methods.

2.3. Role of ML / DL in antennas

ML in the field of antennas reduces the significant computational times of CEM techniques, especially in the optimization of designs with large shapes and more parameters. ANNs use high-performance computers to model EM structures with low computational resources, fewer degrees of errors and in less time. DL is widely used in the antenna research community for remote sensing and inverse scattering (IS) solutions [1]. To find the shape of a scattering structure, IS uses few receiving antennas. DeepNIS is a DNN for nonlinear EM IS, which uses a less number of receiving antennas.

3. Review of ML/DL algorithms

ML uses statistics, data searching, interpolation, and optimization for better decision-making. These approaches are [3]:

- ANNs

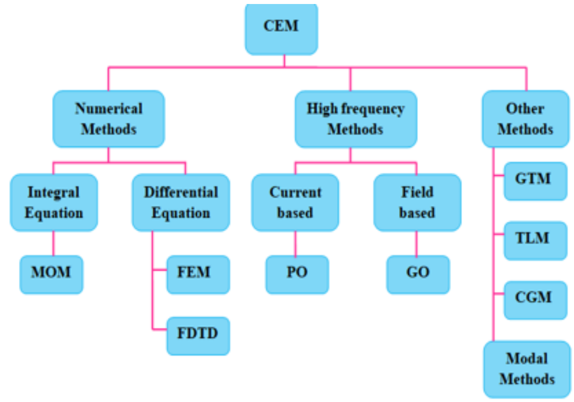

Fig. 2 CEM Techniques

- Evaluating hypotheses
- Decision tree learning
- General to the specific ordering
- Concept learning
- Bayesian learning
- DNNs
- Instance-based learning
- Computational learning theory
- Combining inductive and analytical learning
- Analytical learning
- Support vector machines (SVMs)
- Radial basis functions (RBFs)
- Genetic algorithms (GAs)
- Learning sets of rules
- Reinforcement learning

3.1. Categories of machine learning

ML transfers the mathematical optimization problems to data-driven problems with less computational complexity. ML is broadly classified into three categories [4, 5]. They are,

3.1.1. Supervised learning

This learning task works on labeled input-output pairs to make predictions on unseen input. The training data is associated with targets or labels, whereas they are missing in testing data. The supervised learning is further classified as follows:

3.1.1.1. Regression

In this method, unseen data labels are predicted using available data. Regression algorithms are least absolute shrinkage and selection operator (LASSO), linear regression (LR), kernel ridge regression (KRR), and support vector regression (SVR).

3.1.1.2. Classification

In this method, data is labeled from a finite set of classes. This method includes binary classification and multi-class classification.

3.1.2. Unsupervised learning

This method predicts labels for new data based on the unlabeled datasets. Here there is no difference between

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training and testing data. Unsupervised learning is further classified as follows.

3.1.2.1. Clustering

Clustering is used for large datasets. It identifies regions or groups within the datasets.

3.1.2.2. Dimensionality reduction

It is also called manifold learning. Here the dimensions of the data are reduced without compromising the main features of the initial data.

3.1.3. Reinforcement learning

Here the learner is an agent who interacts actively with the learning environment to aim for a common goal. This paradigm is used in optimization, cognitive sciences, and control theory. Markov decision processes (MDPs) are widely used in this field. Figure 3 shows types of ML.

3.2. Artificial and deep neural networks

Along with standard CEM methods, ANNs are used by FEM to minimize the energy function. MoM also uses ANNs because of their stability. ANNs find applications in distributed computing to solve complex EM problems. To speed up FDTD, ANNs were also used. Neural Networks or ANNs are designed to function like the human brain. It is made of many perceptron.

3.2.1. Perceptron

The artificial neuron or node has input and output. It is represented by the mathematical function. Generally, a biological neuron in ANN is called as a perceptron. It is a single-layer neural network. Figure 4 shows a model of the perceptron. Perceptron is represented mathematically as follows

$$y = \sum_{i=0}^{n} w_i x_i$$

3.2.2. ANNs

The information that flows through the system affects the designed ANN because it learns and improves the property. Figure 5 shows the types of ANNs. ANN has three layers: the input, hidden, and output layers. Figure 6 shows the structure of ANN and DNN.

3.2.3. DNNs

DNNs belong to the ANN family. It consist of three or more hidden layers [7].

3.3. Machine learning frameworks

The ML frameworks were built on optimized codes written in Java, R, Python, etc., which offer fast and flexible usage of various algorithms [4]. Some of the frameworks are as follows.

3.3.1. Regression models with learning algorithms

These algorithms [7] helped in deriving the nonlinear relationship between the geometrical parameters and antenna characteristics. The popular ML algorithms used in antenna design are ANN, SVR, Gaussian Process Regression (GPR), LASSO, LR, Broad learning system (BLS), and KRR.

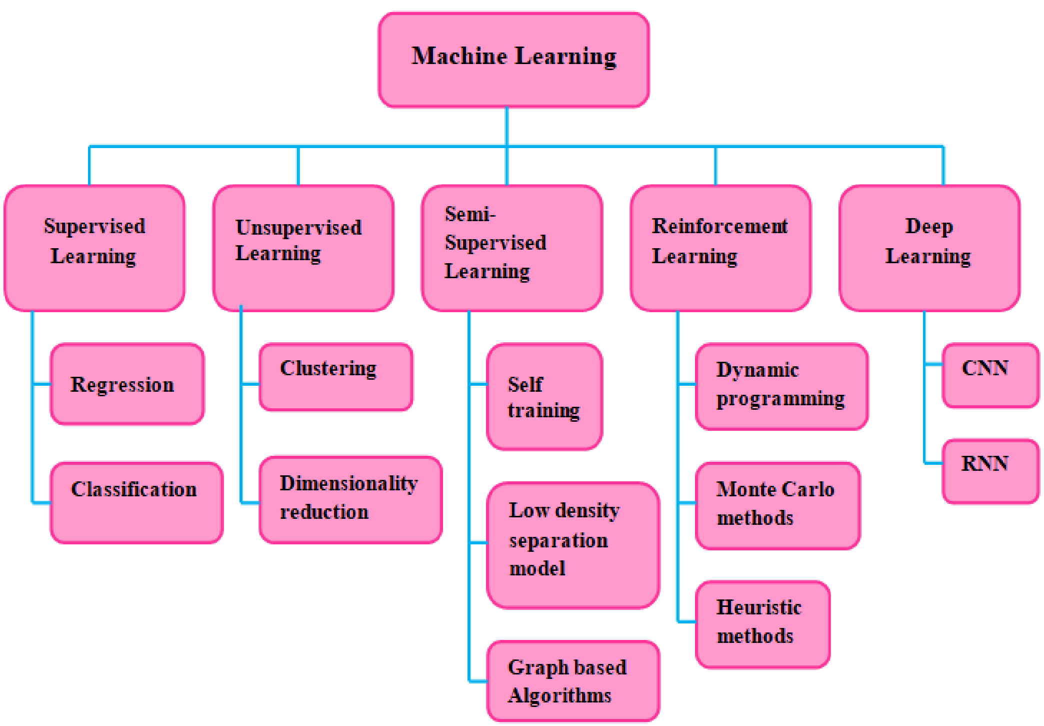

Fig. 3 Classification of Machine Learning

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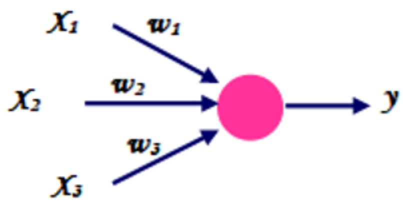

Fig. 4 Perceptron model

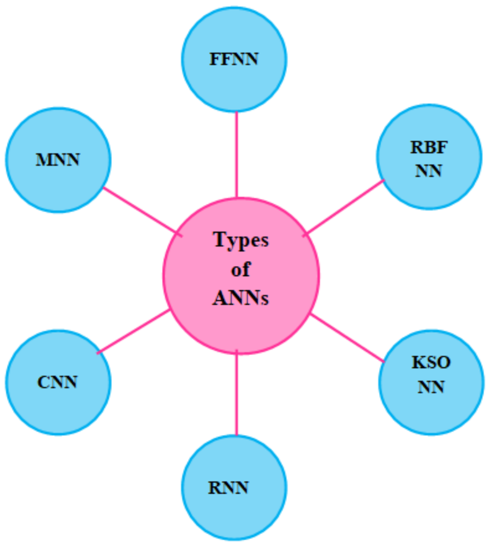

Fig. 5 Classification of ANNs

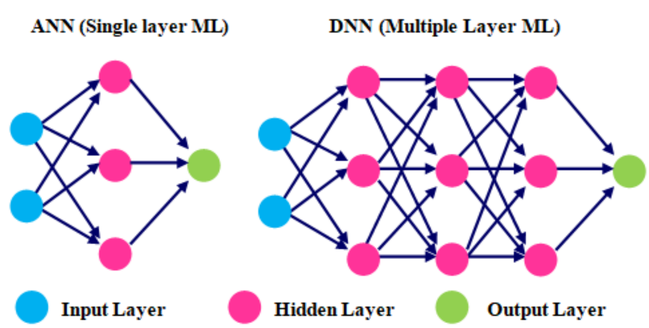

Fig. 6 Structure of ANN and DNN

3.3.2. Training ML models with optimization algorithms

Optimization algorithms are used to find the bias parameters and optimal weight for the ML model. They are used in the training process of the ML models to find the optimized values of the parameters and to reduce the cost function. The optimizers in antenna design are as follows.

3.3.2.1. Gradient descent (GD)

GD updates the parameters after evaluating the gradient of the complete dataset hence GD algorithm/batch is slow. On a non-convex surface before converging to the global minimum, GD is stuck in local minima. Stochastic gradient descent (SGD) serves as an alternative for this.

3.3.2.2. Adaptive moment estimation (ADAM)

ADAM is a computationally efficient algorithm. Here for each parameter, the learning rates are computed.

3.3.2.3. Levenberg Marquardt (LM) algorithm

LM is used for nonlinear least-squares estimation problems with a local minimum of a function. It is a batch form trust-region optimization. It combines GD and Gauss-Newton iterations; it is faster than vanilla GD.

3.3.2.4. Bayesian regularization (BR)

BR trains ANNs instead of error backpropagation over lengthy cross-validations. Bayesian regularized ANNs are difficult to overtrain and overfit.

3.3.2.5. Evolutionary algorithms

These are used in global optimization; they are inspired by the evolutionary process and behavior of living creatures. They include GAs, differential evolution (DE), particle swarm optimization (PSO), etc. and are used in electromagnetic optimization.

3.3.3. Predicting antenna parameters with ML models

Initially, the database is created by simulations. Then the dataset is classified as training, cross-validation, and test sets. An ML algorithm is selected to learn from the data. Predicting output values for desired inputs is done after training and testing the model. Predictions are made at high speeds with low error margins. The metrics to quantify errors are

- **Output error**

It is the difference between output obtained through simulations and output through predictions made by the ML model. It is formulated as

$$e_o = y_d - y_p$$

where,

e_o = Error in output
y_d = Output desired
y_p = Predicted output

- **Mean square error (MSE)**

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

Where, N = Training sample size
The error percentage is given by

$$Error\ \% = \left|\frac{y_d - y_p}{y_d}\right| \times 100$$

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

Researchers used various ML algorithms to design antennas presented in Table 1. The resonance frequency (f_r), permittivity, and height of the substrate are used as input parameters to obtain the dimensions of the rectangular microstrip patch antenna (RMPA) using multi-layer perceptron (MLP) and RBF [8]. The optimization of operational bandwidth, input impedance and f_r of RMPA was done using SVR [9]. In [10], gain, f_r, and VSWR were obtained with the length and width of RMPA using SVR with a Gaussian Kernel. In [11], the slot size and position were predicted using SVR and ANN models. In [12], a printed antenna was designed based on the resilient backpropagation (RPROP) algorithm, feed-forward backpropagation (FFBP) algorithm, RBF, and LM algorithm. These were trained and

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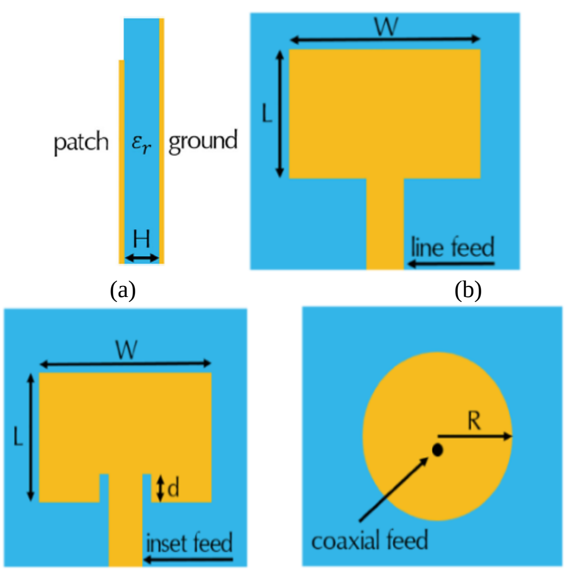
tested using MATLAB. Here, input parameters like patch dimensions, dielectric constant, and substrate thickness are taken to predict output parameters like f_r of the antenna. In [13], ANN was used for designing a circular microstrip patch antenna (CMPA) to determine radius 'a', directivity, and feed position by an MLP model. In [14, 15], f_r of CMPA was predicted based on the patch thickness, radius, and dielectric constant of the substrate. Figure 7 shows the structures of RMPA and CMPA. In [16], the feed gap of a circular monopole antenna was obtained to operate within a particular band of frequency, modeled by ANN. In [17], a two-slot RMPA was implemented using RBF and MLP based ANN models. In [18], a broadband mm-wave substrate integrated waveguide (SIW) cavity-backed slot antenna was implemented using the GPR algorithm. In [19, 20], Kriging Regression was used for reflector array antennas.

Another side, some researchers focused on lodging ML models into optimization algorithms to improve the performance of an antenna, which leads to reduced simulation time. A comparison of antennas along with the used optimization and ML algorithms are presented (see Table 2).

Table 1: Reported antennas with used ML algorithms

Ref.	Antenna Type	ML algorithm
[8, 12]	RMPA	ANN
[9, 10]	RMPA	SVR
[11]	RMPA	SVR, ANN
[13-15]	CMPA	ANN
[16]	Monopole antenna	ANN
[17]	two slot RMPA	ANN
[18]	SIW	GPR
[19, 20]	reflector array	Kriging Regression



(a) (b) (c) (d)

Fig. 7 (a), (b), (c), (d) Rectangular and circular patches with different feeds

Table 2: Reported antennas with both optimization and ML algorithms

Ref.	Antenna Type	Optimization Algorithm	ML Algorithm
[21, 22]	Slot Antenna	Space mapping	BSVR
[23, 24]	Ring monopole Antenna	GA	Interpolation
[25]	Inter chip Antenna	SMA-DE	GPR
[26]	E shaped antenna	DE	Kriging
[27-30]	Stacked patch Antenna	PSO	ANN

5. Application areas of AI in antennas

The application areas of AI in antennas are MIMO antenna selection for diversity purposes [31], Reconfigurable intelligent surfaces [32, 33], wireless localization, adaptive nulling, beamforming architectures, calibration, element failures, and multi-input and multi-output (MIMO) applications. These are discussed briefly as follows.

5.1. Wireless localization

In wireless localization, the positions of desired targets are investigated for navigation and tracking purposes. The most commonly used AI techniques are CNNs and SVMs for active localization, in which the target holds the device that sends a signal in some form. In a device-free localization, the target does not hold the device.

5.2. Adaptive nulling

In a cylindrical array, adaptive nulling identifies nulls in the pattern by using the least significant bits of the element weights while minimizing the total output power. An ML algorithm and DBF architecture are required to maximize the signal to interference ratio (SIR). This method not only reduces the cost function but also used in multipath and noisy environments. Adaptive nulling uses beamforming with an array of software-defined radios (SDRs) and Gas [34].

5.3. Beamforming

An active electronic scanning array (AESA) with an N-element is good one for standard beamforming. It performs scanning of the main beam and reduces sidelobe levels. This technique limits the reconfigurable and adaptive functions and shows poor resolution over the digital beamforming (DBF) architecture replaces the software beamforming with RF beamforming in the computer. Now-a-days, SDRs are used in DBFs. This SDR performs cognitive sensing of the environment along with adaptive nulling. Figure 8 and 9 show SDR beamformer and its setup respectively.

5.4. MIMO communications

MIMO increases the overall capacity of a system. MIMO with DL algorithms are to exploit continuous aperture phased (CAP) MIMO transceivers and channel state information (CSI) estimation [35]. AI finds applications for analog, hybrid and digital beamforming in MIMO smart antenna arrays. Situational awareness strategy and ML techniques are combined to learn information about the beam from previous observations and then reconfigure the array of antenna for mm-wave vehicular applications. Figure 10 shows the architecture of the CAP MIMO antenna.

5.5. Element failure

It is the degradation of performance but not a system failure. By reconfiguring the array beamforming network, the degraded performance is compensated. Here initially, the defective elements are identified. Some of the AI methods proposed for this task are SVM, GAs, NN; case-based reasoning (CBR). Here, even in the case of failure of one element, the radiation pattern of a tested antenna is the same as the reference one [36]. Figure 11 shows radiation characteristics of GA optimized array.

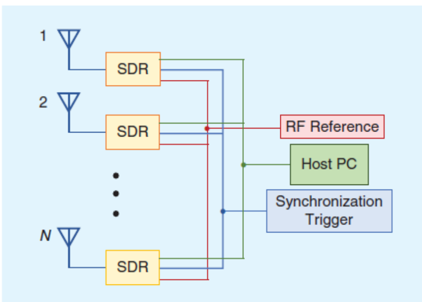


Fig. 8 Block diagram of an SDR beamformer [34]

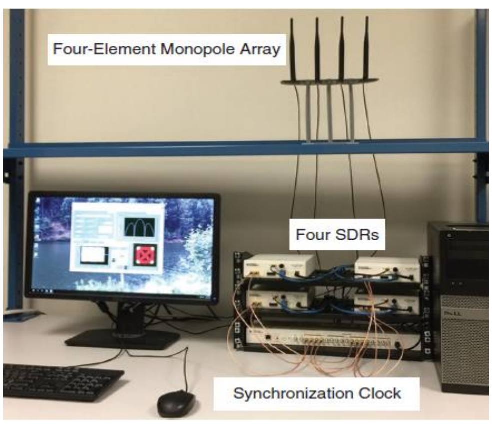


Fig. 9 The setup of the 4-element SDR beamformer [34]

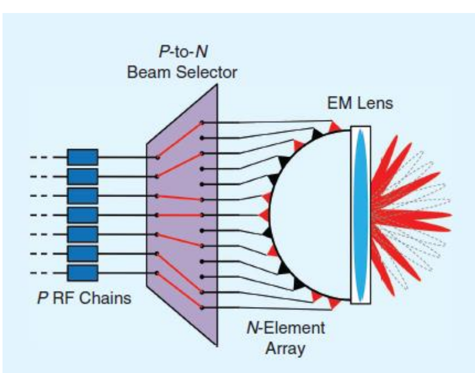


Fig. 10 The architecture of CAP MIMO antenna [35]

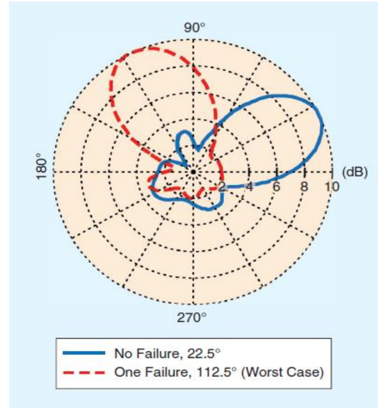


Fig. 11 Radiation characteristics of GA optimized array [36]

5.6. Array Calibration

In antenna arrays, calibration is required for the hardware to avoid deviations in the pattern. The time division duplexing allows massive MIMO to use the same channel for uplink and downlink. Reciprocity holds for the channel transfer function between the transmitter and receiver in both directions. Practically, variations in the phase and amplitude of RF chains will upset the reciprocity of two communicating devices, but customized ANNs overcome this issue. In a testing setup, a base station emulator connects with ports via physical cables for each antenna to the device under test (DUT). In a wireless method, the test signals are first sent over the air to the desired antenna port and then compensate for the transfer matrix (H) between the DUT and testing setup [37]. For a large number of antennas, the PSO provides a scaled solution. Figure 12 shows GA based system for array calibration.

6. Conclusion

AI has many applications in antennas. The significant contribution of AI is to tackle nonlinear and large problems with numerous variables. It is good to adapt to noisy and multipath environments. It is understood that ANNs and DNNs have played a significant role in the research area of ML/DL techniques over traditional CEM techniques. An ML/DL technique in complex antenna design CEM tools

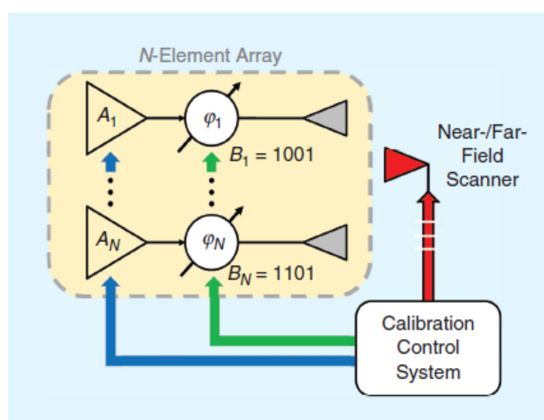


Fig. 12 GA based system for array calibration [37]

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improves the performance characteristics and reduces computational time. This paper also provides the role of AI/ML/DL in antenna design and analysis. The comparative study of various research papers that have employed ML/DL algorithms for their design and optimization is also presented.

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