

Machine Learning in Electromagnetics: A Review and Some Perspectives for Future Research

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Abstract—We review machine learning and its applications in a wide range of electromagnetic problems, including radar, communication, imaging and sensing. We extensively discuss some recent progress in development and use of intelligent algorithms for antenna design, synthesis, and characterization. We also provide some perspectives for future research directions in this emerging field of study.

Keywords—*Electromagnetics, Artificial Neural Network, Machine Learning, Deep Learning*

I. INTRODUCTION

In the past few years, there has been growing interest in machine learning (ML), more specifically artificial neural networks (ANN) and one part of its broader family - deep learning (DL). To date, ML and DL have been demonstrated to be effective in image classification, speech processing, and other information processing tasks. Very recently, ML and DL have been further extended to complex electromagnetic problems, such as structural design and optimal parameter extraction for antennas, beamforming algorithms for adaptive antenna arrays, and data interpretation for radar and MIMO systems. Although many ML and DL algorithms have been proposed, choosing the most appropriate one for a specific electromagnetic problem is still an open-ended question. A comprehensive review of applications of neural network (NN) in smart antennas has been conducted in [1]. The advantages of NN-assisted antenna systems reside in the reduced computational complexity and time, lower cost compared to alternatives, and highly accurate data analysis. In that review paper, results predicted by ML and DL models agree quite well with theory, numerical simulation, and measurements.

II. DESIGN AND ANALYSIS

Typically, in order to have a fully trained NN, one needs to provide a sufficiently large set of data points, i.e., inputs and their corresponding outputs. For antenna designs, this data set can be built by intensively performing numerical simulations for different inputs and/or their combinations. In [2], design goals and objectives (e.g., resonant frequency, directivity, and efficiency) as functions of geometric parameters of a microstrip antenna (e.g., slot and gap) have been investigated using the intelligent method. Microstrip antennas with different slot sizes and air gaps were first simulated using a commercial software, IE3D, and the corresponding antenna characteristics were recorded to construct the data set for training (and also testing) the NNs. The trained NN took a fraction of second to calculate radiation properties of an antenna with a set of randomly generated design parameters. In [3], the data set was constructed using empirical formulas for a single-feed circularly polarized square microstrip antenna. The results showed that Levenberg-Marquardt (LM) algorithm may help designing a practical antenna with desired operating frequency and bandwidth (or Q -factor). In [4], the a contoured beam reflect array composed of antenna elements was designed using NNs. The method of moments (MoM) was used to generate the training data points. It was shown that the ANN can be faster than the MoM by a factor of 100, when both techniques are used to compute radiation characteristics of an unknown antenna. In [5], an ANN has been used to predict aperture antenna shape, demonstrating capabilities of dynamically producing the desired radiation pattern. In contrast, currently existing numerical approaches take days to analyze the design. This

technique is particularly useful for computing radiation characteristics of a non-uniform aperture shape, which has no closed-form solution.

NN can also be applied to synthesize equivalent material properties. In [6] an ML-based approach has been exploited to obtain the desired material properties of a magneto-dielectric substrate, by means of optimizing the size and volume fraction of constituents. The applicability of each intelligent algorithm depends on the electromagnetic problem considered. For example, a rectangular patch antenna was analyzed in [7] with four types of ANN algorithms. The results show that the radial basis function (RBF) may be the most suitable one for evaluating the resonant frequency.

III. OPTIMIZATION

ML and DL have also been vastly used for the optimal design of antennas. In [8], reinforcement learning was developed for optimizing the antenna tilt angle, showing a ~30% improvement in the sum data rate of the network. A new method, called surrogate model assisted differential evolution for antenna synthesis (SADEA), was presented in [9]. This method involves the Gaussian process ML. Compared to the commonly used differential evolution and particle swarm optimization, SADEA can achieve comparable results, but enabling a 3 to 7 times speed enhancement for the design process. In [10], MoM and genetic algorithm were integrated for conducting performance analysis and optimization at the same time. Such a method may improve the computational efficiency and accuracy of the antenna design process.

IV. DEFECTIVE ELEMENTS

Another issue in the field of antenna design and application is real time adjustment. Large antenna arrays have many applications like sonar, radar and communication. Faulty antenna elements in these large arrays cause distortion in the radiation pattern and other characteristics of the antenna. One method to deal with element failure is calibration systems which might be bulky and costly for a certain application [11]. In [11], an ANN has been introduced as a promising solution to locating the fault elements in a 16-element array from its distorted radiation pattern using a multi-layer perceptron (MLP). The number of the failed elements is assumed to be three, after considering the low probability of more faulty elements in practice. NN can also be applied to modify the pattern distorted because of the failed elements by changing the magnitude and phase of the excitation of each element via ML and SVM [12]

V. BEAMFORMING

Adaptive beamforming, which steers the main beam to the desired angle and cancels the nulls along interference directions, is important in many wireless communication and radar applications. A class of beamforming problems can be approached involving ML.

One of the first applications of the NNs to the beamforming problem was described in [13], where the authors developed a neural-based analog circuit implementation for handling the minimum variance distortion-free response (MVDR) beamforming problem. The Hopfield-type NN was used to find the weights of the uniform linear array (ULA), so as to obtain the optimal array pattern. The main advantage of this approach is the reduced computational time compared to the conventional numerical algorithms. Following this pioneering work, other types of NN were applied to beamforming problems.

In [14], a radial basis function neural network (RBFNN) was used for the same purpose. During the performance phase, the RBFNN produced outputs to previously unseen inputs by interpolating between the inputs used (seen) in the training phase. The results were obtained for 1-D (linear array of 10 elements) and 2-D (8x8 array of isotropic elements) cases. The solution obtained by the NN was compared to the array pattern obtained by the optimal Wiener solution. In both cases, the results obtained by the NN were in a good agreement with the optimal solution.

There have been several works comparing different intelligent methods used for the array synthesis. In [15], the authors applied Elman recurrent neural network (ERNN) and trained it using LM and resilient backpropagation (Rprop) algorithms for the ULA with five omnidirectional elements and half-wavelength spacing. Having compared these supervision algorithms, they concluded that LM, although consuming more memory, can outperform other algorithms.

A hybrid beamforming setup comprising an analog beamforming (ABF) network with adjustable beamwidth followed by a zero-forcing baseband processing block was proposed in [16]. The optimal configuration for the ABF network was selected based on the estimated angle of arrival (AoA) of the various user equipment. AoA was estimated by Capon method or MUSIC. Several techniques of ML, such as k-nearest neighbors (kNN) and support vector classification (SVC), or DL, such as MLP were used. When their classification accuracy was compared, MLP outperformed both kNN and SVM. However, the authors mentioned that it might not be true for the multipath scenario.

In many downlink MIMO applications, DL and deep neural network (DNN) can provide approximate solutions that are similar to those obtained by weighted minimum mean square error (WMMSE) method, while increasing considerably the computational time, especially for a large number of transmitting antennas [17]. In [17], two types of DNN (i.e., supervised and unsupervised learning) were explored and the one with unsupervised training showed better performance.

A novel ML-coordinated beamforming solution was proposed in [18]. In that work, the DL model was used to predict the base stations (BS) beamforming vectors directly from the signals received at the distributed BSs using only omni or quasi-omni beam patterns. The main advantage is that the DL model does not require any training before deployment, as it learns and adapts to the environment. As compared to the baseline solution, the DL-coordinated beamforming achieves a noticeable gain, especially when users are moving with high

speed and when the BSs deploy large antenna arrays. With sufficient learning time, the DL model efficiently adapts to changing environment, yielding a robust beamforming system.

VI. DIRECTION OF ARRIVAL (DOA) ESTIMATION

DoA estimation is another problem that has been solved using ML. So far, many papers devoted to this problem have demonstrated that ML may improve the DoA estimation. Particularly, the deep neural network (DNN) was applied to the case of ULA in [19], making possible the detection of signals coming within a 120 degree sector and showing better performance than multiple signal classification (MUSIC). This methodology was designed for a switched-beam system (SBS) for direct sequence code division multiple access (DS-CDMA) applications. The main advantages over MUSIC are speed and simplicity, whereas a drawback could be the operation in a 120 degree instead of a 180 degrees domain. Later on, in [20], a similar problem was solved for 180-degree sector by modifying the DNN configuration, which also make estimation less insensitive to array imperfections, such as non-ideal sensor design and manufacture error, array installation and inter sensor mutual interference, and background radiation. The proposed method showed better robustness compared to MUSIC.

For electronically steerable parasitic array radiator antenna (ESPAR), the DoA estimation problem was solved by means of SVC in [21]. The one-versus-all classification was done for received signal strength (RSS) values recorded at the antenna's output port. The antenna radiation patterns measured precisely in an anechoic room were used as the training data. The performance of the NN-based method was higher than that of the conventional power pattern cross correlation (PPCC) method.

For the purpose of multiple source tracking, the DoA is done by the family of RBFNN [22], which makes the system capable of tracking several sources with any angular separation, without any prior knowledge of the number of sources. The problem was tackled by dividing the field of view of the antenna into angular spatial sectors, training each network in the first stage to detect signals emanating in that sector, and later activating of one or more networks of the second stage to estimate the exact location of the sources. This method allows dramatical reduction in the size of the training set and locating sources greater than the number of antenna elements.

DNN were applied to MIMO system in [23] to perform DoA and channel estimation. The DNN was first trained using simulation data obtained under different channel conditions (with the aid of the offline learning), and then output data were obtained based on the current input data during online learning process. The mean square error (MSE) of DoA estimation with different training length sequences, learning rate, and batch size was examined and compared with the one when other methods (SBEM Scheme, PA channel tracking scheme, ADMA user scheduling scheme, and compressed sensing scheme) were used. The proposed DL based method had lower error than the others.

VII. CONCLUSION AND PERSPECTIVES FOR FUTURE RESEARCH

Based on the above discussions, ML approaches could be successfully applied to different kinds of electromagnetic problems, with aims of reducing computational complexity, allowing faster real-time operation, and helping to deal with problems of complicated structures when accurate simulation is either impossible or very challenging. Though the performance of the ML-based system depends on the quality of the training data, once the training phase is done, the model can work very fast and accurate.

One main drawback of ML is the large amount of data needed for the training [18]. In turn, this may require a large time to generate the data [9]. Efforts are then required to reduce the number of samples for the training, which may be critical for the use of ML methods for many real-time applications. Intelligent approaches may be developed to augment machine learning methods by making use of prior knowledge stemming from the understanding of electromagnetic problems. Ray-tracing methods [24] provide a way to introduce prior knowledge, while preserving a simple understanding of the basic physical phenomena that are involved. Ray-tracing methods are generally fast and can be applied to electrically large problems. Ray-tracing methods have been applied to find the ray trajectories that most contribute to a specific phenomenon. For example, they have been applied to radar problems in [25]-[27] for identifying the most likely propagation channels in a beamforming application.

VIII. REFERENCES

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