Design of Antennas through Artificial Intelligence: State-of-the-Art and Challenges

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***Abstract*—Antenna is a critical part of the RF front end of a communication system. In this study, we present some of the major applications of artificial intelligence (AI) to antenna design. We review the previous research and applications of several AI techniques such as *evolutionary algorithms*,*machine learning*, and *knowledge representation ontologies*. Applications may vary from antenna design to antenna features evaluation in a research field, which is rapidly growing. Finally, we summarize the challenges of new AI techniques in antenna design based on the current state-of-the-art and predict its future research directions.**

I. Introduction

The application of AI techniques in the antennas domain is common in the literature (see Fig. 1). A major group of AI techniques used in antenna design is the *evolutionary algorithms* (EAs). This article presents a classification of EAs **to mainstream and emerging** with representative algorithms of both types. *Machine learning* (ML) algorithms can also be used in several antenna applications, including the estimation of antenna characteristics, such as the S-parameters and gain or radiation pattern, and their use as surrogate methods. In the latter, ML algorithms are used instead of running computationally intensive simulations using a full-wave simulator software. In this case, the ML algorithm runs in conjunction with an optimizer algorithm (EA or other type). Such methods could reduce the time required to achieve a result of satisfactory accuracy. Moreover, *knowledge representation* has also been used in the antennas domain. This is done by using semantic web technologies like the Ontology Web Language (OWL). It must be pointed out the common antenna design methods have several limitations. For example, the Dolph-Tschebyscheff method is suitable only for equidistant broadside antenna arrays. Moreover, the amplitudes obtained by this method are real numbers, which are difficult to implement in practice.

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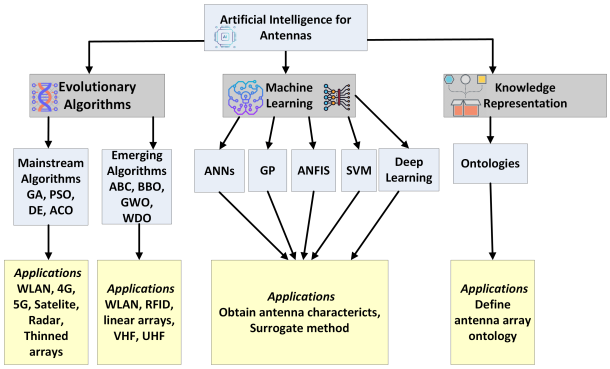

Fig. 1. A classification of AI techniques in the antennas domain.

Another example is the rectangular patch design procedure. This is based on formulas that calculate effective length and width, and thus the dimensions for a specific resonant frequency are obtained. However, this method works only for a rectangular patch, and does not apply to other patch shapes. All the above-described limitations are overcome by the EAs, which are ”black box” optimizers and independent of the objective function (thus, the antenna at hand) form. Review papers found in the literature focus on a specific AI method or antenna type. The authors in [1] describe deep learning applications for antennas. In this context, the authors in [2] describe AI methods for reconfigurable antenna design. In this article, we provide a comprehensive overview of all major AI methods and their applications to antenna design. The main contributions of this article can be summarized as follows:

- We briefly present and list the main benefits and drawbacks of popular AI methods for application to antenna design.
- We review the concept of knowledge representation and discuss possible applications to antenna domain.
- We discuss other state-of-art AI methods that have not been applied to antenna design yet.

II. Evolutionary Algorithms

EAs are nature-inspired metaheuristics such as biology-based metaheuristics. Therefore, EAs typically imitate biological species' behavior and evolution. However, physical/chemistry-based metaheuristics have recently emerged. Moreover, algorithms inspired by the social behavior of humans is also evolving. The common feature

of these algorithms is that an initial population of vectors evolves through iterations by applying different operators.

EAs can be grouped into two large categories depending on their popularity: mainstream algorithms and emerging algorithms. Genetic algorithms (GAs) are one of the most commonly used mainstream methods. Another special type of EAs is the swarm intelligence (SI) algorithm. Swarm intelligence can be characterized as decentralized and self-organized swarm collective behavior. Corresponding SI algorithms include ant colony optimization (ACO) and particle swarm optimization (PSO). Differential evolution (DE) refers to another common and popular family of EAs. DE is a population-based metaheuristic based on mathematical models and does not mimic specific behavior from nature.

A large number of optimization problems exist in the antenna domain. This makes it very difficult for antenna engineers to select an appropriate algorithm for each problem.

As a result, it is worthwhile to investigate new optimization strategies for problems emerging in antenna design and synthesis, which can greatly benefit from the use of EAs. The majority of antenna design issues fall into one of the two categories. The first is concerned with determining the optimal geometry for a particular antenna element, whereas the second is concerned with optimizing the locations and excitation of an antenna array. Other optimization options could be a combination of the aforementioned issues. The antenna application domain contains all the types of wireless communication for example, cellular communications, satellite communications, cognitive radio applications, and wireless networks.

A. Mainstream Algorithms

Genetic Algorithms (GAs) are the most popular metaheuristics in the antenna design domain. GAs typically use crossover, mutation, and selection operators. A crossover operator recombines two or more parents to create a new child. The mutation operator probabilistically alters the current solution. The selection operator refers to the manner in which the parent vectors or chromosomes are selected for recombination. Usually, GAs also include the feature of elitism, that is, the best or more good solutions survive to the next generation. GAs can be real-coded (RGA) or binary-coded (BGA) depending on the problem type. GAs have been applied to almost all types of antennas. The authors in [3] applied both single and multi-objective GA for a 5G base station antenna array design.

Particle Swarm Optimization (PSO) is an SI algorithm that models the behavior of bird swarms, that is, the way swarms of birds search for food. The PSO is a low-complexity algorithm that can be easily implemented in any programming language. In the case of the PSO, we need to set the following control parameters: the cognitive learning factor, the social learning factor. and the inertia weight. PSO is also a very popular algorithm for antenna design. Several PSO variants have been used. Although PSO inherently works in the real space, binary extensions also exist. The authors in [4] apply a modified binary particle swarm optimization (MBPSO) to design a planar wideband antenna array for millimeter-Wave operation.

Differential Evolution (DE) is a global optimizer that uses vectors to evolve using three operators: mutation, crossover, and selection. DE is a mathematical design that is not based on a specific biological phenomenon. The DE variants or strategies found in literature are based on the modification of one or more of these basic operators. The best DE strategy is determined based on the problem type. Moreover, DE is also very popular for antenna design, as it has been widely used, particularly for antenna array design. The authors in [5] introduce a DE algorithm that uses a new encoding mechanism. Their main objective is to design large planar arrays that are unequally spaced and have a minimum interelement distance constraint. Such arrays can find several applications in radar, sonar and satellite communications.

Ant Colony Optimization (ACO) is a nature-inspired algorithm based on the communication mechanism among ants. In nature, chemical pheromone trials are used by ants to communicate with each other. By sensing and following trails with strong pheromone intensities, ants can find shorter distances between nests, and food sources. ACO works by mathematically modeling this behavior. One of the major advantages is that they can be used effectively for solving combinatorial optimization problems. Such problems can be found commonly in the antenna domain, for example, for the design of linear subarrays or for thinned array design. The authors in [6] use a multi-objective lazy ant colony optimization (MOLACO) algorithm for a 3-D frequency selective structures (FSS) design operating in C-band.

B. Emerging algorithms

Biogeography-based optimization (BBO) has has emerged based on the biological domain biogeography. BBO applies mathematical models that predict animal migration patterns. The number of species in a habitat can be estimated using migration patterns. The habitat in the BBO is a vector of unknown variables in the problem to be solved. These variables are referred to as suitability index variables (SIV). Each habitat or vector was assigned a habitat suitability index (HSI) value. HSI represents the fitness value. BBO uses both the migration and mutation operators. The unique feature of BBO in comparison with other algorithms is the migration procedure, that is, the manner in which the vectors exchange information. This feature makes the BBO a good candidate optimizer for solving combinatorial optimization problems. BBO requires the setting of two control parameters, namely, the modification probability and mutation probability. The authors in [7] have applied BBO to a Yagi-Uda antenna design. In this case, the cost function is a single-objective function that uses a weighted sum approach.

Grey Wolf Optimizer (GWO) is an evolutionary algorithm based on models that mathematically represent the grey wolf hierarchy and hunting mechanisms. The preservation of information about the search space during the iteration process is a key characteristic of GWO. GWO has the advantage of not requiring the setting of any control parameter. The GWO algorithm grouped the population into different categories. Therefore, the optimization process, which mimics the social

TABLE I
ADVANTAGES AND DISADVANTAGES OF EAS USED FOR ANTENNA DESIGN.

Algorithm	Advantages	Disadvantages
GAs	Very popular (several codes avaliable)	Requires a lot of time to fine-tune the operators
	High degree of flexibility	Unguided mutation operator
	Easy to parallelize	
	large and wide solution space search ability	
PSO	Easy to code	Several parameters to tune for best operation
	Insensitive to scaling of design variables.	May get trapped into local optima in high-dimensional space
	Efficient global search	low convergence rate
DE	The number of control parameters in DE is very few	May find difficulties in solving problems with non separable functions
	Compared to other EAs, more simple and straightforward to implement	May get trapped into local optima
	Low spaced complexity	
	Guided mutation operator	
ACO	Very efficient for discrete optimization problems	Not suitable for every problem type
	Easy to parallelize	Weak exploitation ability , slow convergence speed
	Easy to apply to dynamic applications	Long computation time and stagnation phenomenon are quite probable.
BBO	Very efficient for combinatorial optimization problems	Poor exploitation ability
	Computational complexity similar to other Eas	Selection of the best members from each generation is not made
	unique, simple and easy to implement	
	Good exploration ability	
	Widely available source code	
GWO	Easy to implement	May get trapped into local optima
	Parameter free-no tuning required	Low exploitation ability
	Widely available source code	
WDO	Works well with antenna design problems	Several control parameters to tune
	Fast convergence	Not tested in several application domains
	Widely available source code	

behavior of a wolf pack, is driven by these population groups. The authors in [8] apply different versions of GWO algorithm to design sparse linear arrays, Yagi-Uda antenna and thinned planar arrays.

Wind Driven Optimization (WDO) is a new physics-based algorithm that predicts atmospheric motion. The primary idea behind the WDO is to use Newton's second rule of motion to describe the movement of air parcels. The WDO has several control parameters to tune: the friction coefficient, air temperature, universal gas constant, Coriolis force contribution parameter, gravitational constant, and maximum allowable velocity. The authors in [9] describe how the tuning of these parameters can be accomplished. Moreover, they apply WDO to several antenna design problems, thus proving the algorithm efficiency. These cases consist of linear antenna array, an E-shaped patch antenna for WiFi operation at 5 GHz, and artificial magnetic conducting (AMC) ground planes. A brief description of the main advantages and disadvantages of the algorithms presented in this section is presented in Table I.

C. Example antenna design case

As an example of EA optimization, we present the results of an antenna for operation in the low THz band 250GHz to 330GHz. The antenna was a modified E-shaped antenna with an additional third slot. Fig. 2 depicts this antenna. The antenna substrate was Rogers5880 with a dielectric constant $\epsilon_r = 2.2$, $tan\delta = 0.001$ and thickness 0.127mm. This antenna type needs the definition of 14 different geometrical parameters. Evidently, such a design cannot be completed without an optimization technique. We apply the DE algorithm using a population size of 20 and a total number of 75 iterations. The final result is a wideband antenna that operates over the entire frequency band. Fig. 2 shows the DE convergence rate graph and the 3D radiation pattern. Additionally, one may notice the both S_{11} and the realized gain frequency response graphs can be observed.

III. MACHINE LEARNING

Machine learning (ML) algorithms, which have the ability to learn from data, have also been used to solve a number of antenna design problems.

Antenna problems require general modelling as a supervised regression task. A detailed review of supervised ML methods in electromagnetics can be found in [10]. In general, three major antenna problem types are addressed by ML algorithms: antenna synthesis, antenna analysis, and Direction-of-arrival estimation (DoA).

In antenna synthesis, a ML algorithm is mostly used as a surrogate method for full-wave analysis. Full-wave EM solvers for modern antennas are time consuming and require additional computational power. In order to save time and computational resources, the use of a surrogate method is common in antenna literature. The whole method can be generally described in the following steps (see Fig. 3).

- **Step 1.** The dataset is generated by varying the antenna geometry and/or the frequency of operation (input data) by running a full-wave EM simulator. The output may be S-parameters, gain, or radiation patterns in one or more frequencies.

TABLE II
ADVANTAGES AND DISADVANTAGES OF ML METHODS USED FOR ANTENNA DESIGN.

Algorithm	Advantages	Disadvantages
ANN	Generic method for modeling any data type	Computationally intensive
	Robust to noise in training data	Prone to overfiting
	May use different training algorithms	No rule for stucture definition
	Models linear and non-linear functions	Does not "understand" the problem
SVM	Very effective in high dimensional spaces.	Selection of an appropriate Kernel function is difficult
	Memory efficient	Poor performance with noise in data
	Handles non-linear data efficiently	Underperform for large data sets
GP	Capture directly the model uncertainty	Very Computationally intensive
	Obtain smooth and nonlinear models	
DL	Work very well with image detection tasks	Very Computationally intensive
	Same DL structure can be applied to different data types	Requires large amount of training data
	Very flexible for future problem adaptation	No rule for suitable DL type selection
	Can use GPUs effectively and parallel	
	Several open source frameworks	
ANFIS	Rapid learning	Type and number of membership functions
	Adaptation capability	The location of a membership function
	Models linear and non-linear functions	Curse of dimensionality
	Inserts rules to the model based on prior knowledge	

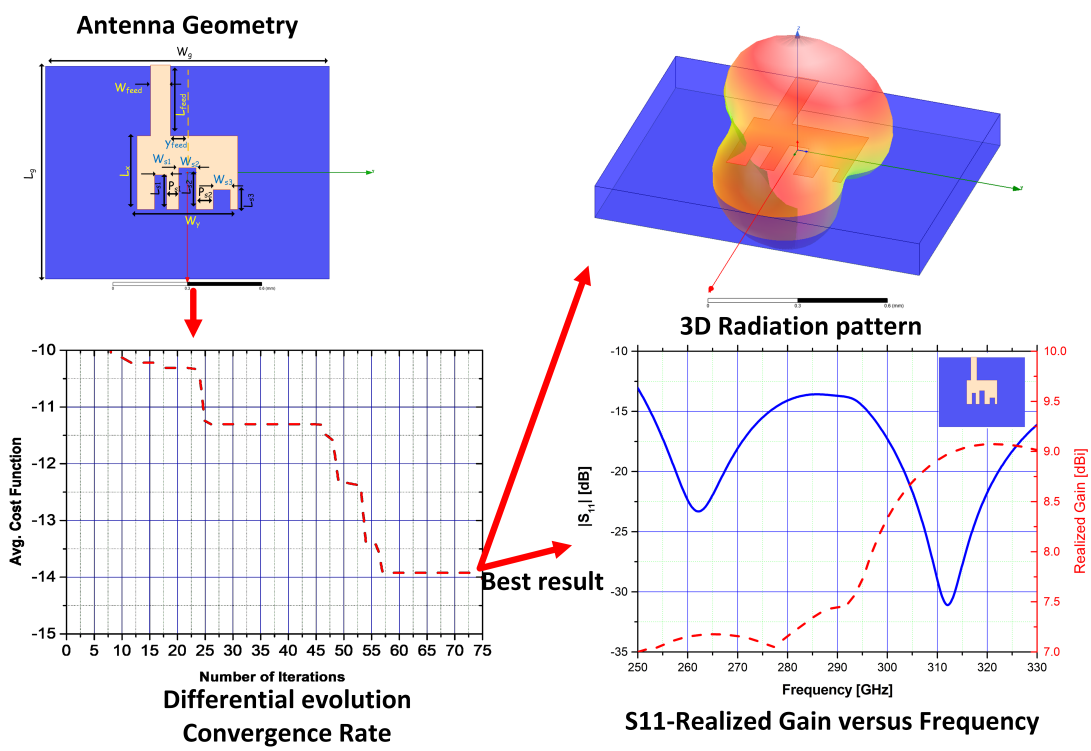

Fig. 2. Example of an wide band antenna design for operation in low THz band (250-330GHz) using the Differential Evolution algorithm.

- **Step 2.** The ML algorithm was trained using approximately 80% of the obtained dataset.
- **Step 3.** Obtain the testing error by using the remaining 20% of the dataset (as a rule of thumb) as input to the ML algorithm. If the testing error is not satisfactory, return to step 1, generate more data, or fine-tune the ML algorithm.
- **Step 4.** Run the ML algorithm instead of the full-wave EM simulator in conjunction with an optimization method (like an EA).
- **Step 5.** Fine-tune the best obtained design by rerunning the full-wave EM simulator

In antenna analysis, a training dataset is also obtained by running full-wave simulations or real antenna measurements. The ML algorithm is trained with these data and is used to predict the values of certain antenna characteristics, such as the radiation pattern, scattering responses, S-parameters, mutual coupling characteristics, and resonant frequencies. It must be pointed out that more complex surrogate models could be build with two or more outputs. Such models could be combined with a multi-objective evolutionary algorithm. In this case several different antenna design cases can be obtained as points in the Pareto front. The case that satisfies better

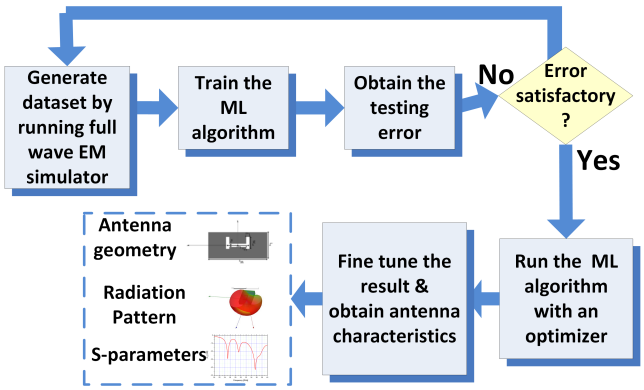

Fig. 3. Use of an ML algorithm in antenna synthesis.

all objective functions can be selected in this case. Another option would be also to define constraint functions as well to find only the Pareto front points that lie in a specific region of interest. Additionally, the surrogate model could also be used to perform a sensitivity analysis, the input parameters are varied with a specific tolerance and we can find the tolerance level of the output(s). Antenna array failure correction is another antenna design case that could use ML models. In this case, one or more elements of an array fail and the antenna array needs to readjust the remaining working elements in order to obtain the same initial radiation pattern. This kind of problem can be modeled as a binary classification problem. Several radiation patterns can be used as training data, which can be classified to working well or not with different element excitations. Finally, in the DoA estimation, the ML algorithm is first trained with DoA data. Then, the ML algorithm is used to determine the optimal antenna array excitation to suppress interference and reduce the sidelobe level (SLL). In other words, the ML model is used as an adaptive beamformer that directs the main lobe of an antenna array toward a desired signal, places nulls in the path of the interference signals, and suppresses the SLL.

Artificial Neural Networks (ANNs) are the most widely used base learners in the antenna domain. The main advantage of neural networks is their ability to find out the relationship among the physical parameters of a problem and the results to which they lead via a complicated physical procedure. Thus, an ANN can substantially determine the function that describes this physical procedure, the closed formulation of which is unavailable. Among others, ANNs perform efficiently in applications, such as data classification, prediction approximation, and signal processing. In a recent study [11], an ANN model was used to simultaneously obtain antenna characteristics such as the S_{11} value, gain, and radiation pattern from three different branches and in conjunction with a support vector machine.

Support vector machines (SVMs) are another large category of ML algorithms used in antenna problems. They are used in both classification and regression applications. One of the advantages of SVM is the use of convex quadratic programming, which is a global optimization process. The theoretical framework of SVMs is statistical learning theory. As it is reported in [2], the SVM was used to solve the antenna array element failure problem.

Gaussian process (GP) has also recently been used as the main ML algorithm for antenna problems. The main advantage of GPs is that they are considered to be equivalent to ANNs. However, GPs are easier to implement and require the training of fewer parameters than ANNs. The authors in [12] used GP regression to model planar antenna input characteristics. The authors used GP to reduce the computational time by 80%. The input parameters were the antenna geometry and the output was the S_{11} value.

Deep Learning (DL) is a special type of ANN that uses several hidden layers to model information. DL has become very popular over the last few years. DL has emerged as an application for image recognition; however, it has spread across several application domains, including antennas. In a recent study, the authors presented a surrogate modelling technique using a pyramidal deep regression network [13]. The authors designed different patch antenna types by using this framework.

ANFIS is a type of fuzzy inference system (FIS). ANFIS combines the advantages of both ANNs and FIS. The basic goal of ANFIS is to use a learning algorithm and input-output data sets to optimize the parameters of the corresponding FIS. The use of ANFIS for antenna problems is quite popular. Among others, the problem of the performance prediction of pyramidal and conical corrugated horn antennas has been addressed in the literature. Again, the input parameters are the antenna geometrical variables, and the output parameters are the S_{11} value and the radiation pattern.

Table II provides an overview of advantages and disadvantages of ML methods used for antenna design.

IV. Knowledge Representation

Semantic Web technologies are a knowledge representation form for web resources. The main objective of Semantic Web is to give information that is machine readable. Thus, by using semantic web technology both machines and humans can process and share data.

Semantic web defines four layers for data representation. Namely, these from the bottom to the top are Extensible Markup Language (XML), RDF (Resource Description Framework), Ontology, and Logic. Web Ontology Language (OWL) is the main language for defining ontologies in the web. An ontology in OWL is crated by defining classes (that have instances or individuals), and properties (which have data values). All of these are accessed and stored as Semantic Web documents. Constraints on these classes and properties can also be applied that enrich the expressive power of OWL. Ontologies are formalized word dictionaries that are shared by a group of users and frequently cover a single area. By outlining how each term in the ontology interacts with other concepts, they describe the definitions of each term.

In 2012 W3C defined OWL2 that defined additional features and increased the expressiveness of the language. Any OWL 2 ontology can alternatively be seen as an Resource Description Framework (RDF) graph. OWL 2 defines three

TABLE III
FUTURE RESEARCH DIRECTIONS IN AI FOR THE ANTENNA DOMAIN.

AI Category	Technique	Feature in Antenna domain
EAs	Memetic algorithms (MAs)	Provide balance between global exploration and local exploitation, faster and accurate antenna optimization
	Self-tuned algorithms	Save computational time for antenna optimization
	Meta-optimizers	Extract generalizable results and develop meta-level-based applications for antenna design
ML	Meta-learning or few shot learning	Find the best starting parameters for the surrogate ML model, use fewer training data to obtain result
	Data generation methods (e.g. GANs)	Generate additional data for surogate model training, save computational time
	Ensemble learning	Combine ML models to obtain more accurate results for antenna design'
	Lightweight DL techniques (e.g. BNN)	Save computational time, less accurate results, obtain antenna designs faster
KR	Ontologies	Machine automated design of antennas

sub-languages or profiles in OWL terminology.These are *OWL 2 EL*, *OWL 2 QL*, and *OWL 2 RL*. Every profile makes different tradeoffs to OWL's expressive capacity in exchange for various computational and/or implementational advantages For all common reasoning tasks, OWL 2 EL enables polynomial time algorithms; it is especially well suited for applications requiring very large ontologies. OWL 2 QL makes it possible to respond to conjunctive queries in LogSpace with the help of conventional relational database technology. It is especially well suited for applications where relatively lightweight ontologies are used to organize large numbers of individuals and where it is useful or necessary to access the data directly via relational queries. It is particularly well suited for case where relatively lightweight ontologies are used to organize huge class instances and where it is advantageous or necessary to directly access the data using relational queries. OWL 2 RL is especially well suited for applications where it is beneficial or necessary to act directly on data in the form of RDF triples and where reasonably lightweight ontologies are used to organize huge numbers of individuals. Additionally, OWL 2 RL makes it possible to use rule-extended database technologies that work directly with RDF triples to implement polynomial-time reasoning algorithms. KR in the antennas domain is very new. In [14], the authors have proposed an example of an OWL DL ontology for antennas. This ontology is on the concept of antenna array. This use of ontologies in the antennas domain has the potential to be a first step towards the machine automated design of antennas.

V. FUTURE RESEARCH DIRECTIONS

EAs are a constantly growing research field. It is often helpful to introduce new optimizers that perform well in a specific optimization problem. For example, they could be hybrid algorithms that use features from two or more algorithms. Algorithms that are hybrids of EAs with local optimizers are termed as memetic algorithms (MAs). MAs are based on Dawkins's concept of memes. The use of the local optimizer in MAs helps provide good exploitation ability with fewer objective function evaluations than normal EAs. Moreover, the EA, which is a global optimizer, may generate good-quality solutions that can be used as initial starting points for the local optimizer. Thus, based on this balance between global exploration and local exploitation, MAs have the potential for high efficiency. MAs could be applied to any antenna design problem. For example they could solve a patch antenna design problem.

Additionally, optimization methods that are self-tuned or parameter-free are very useful for avoiding time-consuming control parameter-tuning tasks. Otherwise, control parameter tuning can be performed at a meta-level using, for example, a meta-optimizer. This tuning can be performed by a multi-objective algorithm that acts as the meta-optimizer. Using this approach, it is feasible to extract generalizable results that can be used to develop meta-level-based applications in addition to finding suitable parameter sets. Meta-optimizers would require high computational load, so they could be applied to an antenna design problem that can solved analytically. For example to an antenna array design problem.

The high amount of data required for most machine learning methods can be overcome using two different approaches. The first is the use of a metamodel for model definition and tuning. This meta-level can be applied to machine learning by using a meta-learning approach. This method has the potential to built sufficiently accurate models. Meta-learning also refers to a group of techniques for learning new concepts using only a few data points, and is often known as few-shot learning. Moreover, meta-learning methods include Model-Agnostic Meta-Learning [15] (MAML). MAML is capable of determining the best starting parameters for the network model, resulting in good outcomes for the few-shot task after only a few gradient update steps. The MAML is an excellent meta-learning method for effectively resolving few-shot problems. Meta-learning would save computational time, so it could be applied to an antenna design problem combined with a full-wave simulator.

The second approach is to use ML methods to generate more data for antenna optimization. This approach has the advantage of avoiding the time-consuming part of data generation using commercial EM solvers. Data generation methods include the use of generative adversarial networks (GAN). However, this approach is not straightforward because GANs have emerged for image-processing applications and are not directly tuned

for regression tasks. Therefore,their suitable application to antenna design tasks depends on the antenna type, and may include difficulties to overcome. Again this approach would save computational time, so it could be applied to an antenna design problem that requires heavy computational load.

Ensemble learning techniques are another option for antenna engineers to define their own method that combines results from other existing methods to produce a more accurate final result. If more accuracy is required in surrogate modeling, then this approach could be used. Finally, the use of more lightweight DL techniques, such as binary neural networks (DL networks with weights of 1 or -1), is another open issue for antenna design. Such models have the advantage of significantly reducing the computation costs. However, this is at the expense of the accuracy. Once more, this method would reduce the amount of CPU time required, thus making it suitable for antenna design cases that demand a lot of processing power.

Table III lists the above-described methods. Overall, the entire AI domain is a promising direction for antenna applications, with both supervised learning and optimization tasks.

VI. Conclusion

In this article, we review the major AI families for the antenna domain. We grouped the techniques used into three distinct groups: EAs, ML, and KR. Popular evolutionary algorithms and emerging algorithms that have been applied to fewer antenna design cases are reviewed. Moreover, we discuss and present the most widely used ML methods in the antenna domain. KR using the OWL language was also considered. Finally, future research directions are briefly outlined, focusing on additional algorithms and ML methods that can be applied in antenna design.

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