Guest Editorial Machine Learning in Antenna Design, Modeling, and Measurements

I. Introduction

MACHINE learning (ML) is the study of computational methods for improving performance by mechanizing the acquisition of knowledge from experience. As a modern data-driven optimization and applied regression methodology, ML aims to provide increasing levels of automation in the knowledge engineering process, replacing much time-consuming human activity with automatic techniques that improve accuracy and/or efficiency by discovering and exploiting regularities in training data. Indeed, many ML and data-driven methods, such as conventional artificial neural networks (ANNs), were introduced and studied within electromagnetics a few decades ago. However, these past studies did not benefit from the most recent advances in ML, which have been driven by the present confluence of improved hardware performance at lower cost, advanced network algorithms and architectures, data science, and considerable efforts dedicated to advancing the computational electromagnetics (CEM) benchmark. Today, a broader family of ML techniques based on ANNs has been developed. Examples include deep neural network (DNN), convolutional neural network (CNN), recurrent neural network, generative adversarial network, and deep reinforcement learning, which have been successfully applied to different engineering and science problems, ranging from image and video recognition, social media services, virtual personal assistant to autonomous vehicles, to name a few. This naturally suggests that applying ML to real-world electromagnetic problems could be one of the emerging trends in ML and artificial intelligence (AI) [1]–[4]. Indeed, ML has been becoming an important complement to existing experimental, computational, and theoretical aspects of electromagnetics.

In designs of antennas [5], arrays [6]–[8], and artificial electromagnetic media (e.g., metamaterials, metasurfaces, electromagnetic bandgap structures, and frequency selective surfaces [9]), ML offers a wealth of techniques to discover optimum structures and geometric patterns from high-dimensional stochastic data. ML tools are expected to become the cornerstone of antenna designs in the near future. Novel ML methods leveraging randomized numerical and experimental data have been shown to have the potential to become powerful optimization tools and enablers for designing complex antennas, arrays, and functional electromagnetic structures, which are difficult to design with traditional analytical and numerical methods. Many goals in modern antenna and metamaterial designs, spanning temporal, frequency and spectral domains, and a large number of constraints pose serious optimization issues. These electromagnetic problems are challenging, as they usually arise in nonlinear and multiscale forms and strong mutual correlation (coupling), resulting in high-dimensional and nonconvex optimization landscapes. Fortunately, ML now opens the possibility to tackle these traditionally intractable optimization problems in an effective and time-saving way. Since the ML tools are rather easy to use and do not require expert knowledge, they are quite appealing to antenna engineers; arguably, some see this as a potential downfall. Despite the great potential, it is important to emphasize that these algorithms must be used properly and that no single tool can solve all tasks, as learned from the collected articles in this special issue. Similar to the caution with electromagnetic simulation tools (i.e., sometimes a blackbox), one must adopt an equivalent philosophy for the use of ML and data-driven design and optimization tools and use them properly with prior knowledge and validation. The collected articles may provide a guide to important aspects of the ML practice and the specific nature of usability.

In the field of CEM, there are interesting parallels between the rise of ML in recent years and the rise of high-performance computing a few decades earlier. Both approaches provide powerful tools for obtaining deep insights in electromagnetic physics and analysis of sophisticated electromagnetic propagation and scattering problems, enabling the community to address scientific and engineering questions at an unprecedented scale and a broader scope than what was previously possible. ML-assisted CEM techniques can provide another valuable perspective for complementing more traditional approaches and enhancing the speed and accuracy of existing CEM algorithms. To date, many generative AI and ML methods have been proven successful for scattering [10], inverse scattering [11], and imaging [12]–[14] applications, radar signal processing, and reinforcement strategies for CEM. It is reasonable to believe that fusion of ML algorithms, measurement data and numerical modeling will pave the way for building new generations of antenna and radar systems, as well as ultrahigh-performance and multidimensional CEM solvers. The papers published in this Special Issue may convince people that ML and data-intensive analysis will have a similar impact, complementing other well-established CEM techniques to expand this field of study.

The objective of this Special Issue is to highlight several promising avenues of ongoing research to integrate ML and data-driven AI techniques in the field of antennas and propagation. Specifically, it aims to provide a broader perspective,

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outlining recent successes, opportunities, and open challenges for ML and their potential applications to antennas, radar, scattering, and propagation problems, as well as to increase their visibility within the electromagnetics community.

II. Main Contributions of the Papers in This Special Issue

The papers in this Special Issue can be categorized into five groups based on their engineering applications. These include AI applications for antenna design, antenna arrays, metasurfaces, CEM, and other related applications.

A. AI for Antenna Design

In [A1], Li *et al.* presented a new Online Data-Driven Enhanced-XGBoost strategy for antenna optimization. The paper starts with a rich bibliographic analysis presenting and comparing background strategies and existing approaches. Then the main method is presented and analyzed in detail. A set of verification experiments concludes the contribution by showing the practical relevance of the new technique.

In [A2], Shi *et al.* proposed an intelligent antenna design system, which can recommend an appropriate type of antenna and provide specific geometrical parameters for the chosen antenna based on the desired performance specifications. The proposed system consists of an intelligent model based on a support vector machine to recommend the antenna type and a stacking ensemble learning model to provide corresponding structural parameters. The paper presented a test case to demonstrate the use and effectiveness of the system.

In [A3], Fu *et al.* combined two models based on ML with a particle swarm optimization algorithm for antenna synthesis applications. After a study of existing literature, the work delineates the new idea by comparing it with standard particle swarm optimization approaches. The new scheme is further analyzed in each of its components, and the paper concludes with a rich numerical experiment section where the strategy is applied to several design case scenarios.

The contribution by Chen *et al.* [A4] focuses on antenna design, accelerated via a multibranch ML strategy. The paper starts with a bibliographic analysis followed by a modular description of the main components of the newly proposed scheme: regression approaches, prescreening strategies, and final stages. The paper concludes with a validation and verification section where antenna designs of several radiating structures are considered and the performance of the newly proposed approaches is thoroughly analyzed and discussed.

In [A5], Sharma *et al.* proposed an ML-based optimization method based on a Gaussian process regression and an ANN, which can be an efficient alternative to traditional optimization methods when designing complex antennas with many design parameters. The authors showcase a multibeam monopole antenna surrounded by an inhomogeneous 2-D array of dielectric bricks, whose spatial distribution is improved by an ML-based optimization methodology. This method can provide a complete relational model between design parameters and performance specification, which can be readily adapted to different optimization goals, which is not feasible with a genetic algorithm (GA) and other popular heuristic optimization methods.

In [A6], Liu *et al.* employed a knowledge-based ANN model, which includes a forward and an inverse neural network, to design antennas by considering multiple performance indices. The inverse neural network is exploited to predict antenna parameters, while the forward neural network provides the required training dataset to the inverse neural network. The knowledge-based ANN designed circularly polarized lens antenna fabricated by the 3-D printing technique exhibits several impressive features, such as wideband, good axial ratio, and high gain.

In [A7], Stanković *et al.* presented a generalized approach for antenna design and optimization based on the consensus of results from several independently trained DNNs. The model is composed of multiple DNNs, with each DNN giving its decision according to the same input. The final decision is made by counting on the consensus of the output of all DNNs, in order to reduce the uncertainty of the result from a single DNN when dealing with a complex design. An inverse design experiment considering the Yagi-Uda antenna demonstrates that the proposed model can outperform the conventional single DNN model as it can provide accurate estimates of the optimal geometric configurations with fewer training iterations and a much smaller dataset.

In [A8], Liu *et al.* presented a prior-knowledge-guided deep-learning-enabled synthesis method that utilizes a conditional deep convolutional generative adversarial network to strategically guide and speed up the synthesis of antennas based on prior knowledge including well-known theorems and experience in antenna design. As a representative example, this method is employed to enhance the transmission bandwidth and the phase shift range of a Ku-band metalens antenna. Remarkably, the conditional deep convolutional generative adversarial network-designed metacells enable a more than 50% increase in the gain bandwidth, when compared to traditional metacells, such as the Jerusalem cross.

In [A9], Mou *et al.* proposed an optimization method based on the near-field pattern synthesis for building a beam-scanning reflector antenna with maximum radiation efficiency. Different from the conventional conjugate field matching method, this optimization model combines the radiation efficiency and the power amplifier efficiency as a new criterion called radiation power efficiency. A series of numerical simulation data with all ON-state power amplifiers is first generated using Ansys HFSS. Then, the ON–OFF state of each power amplifier is adjusted by using the support vector machine such that the reflected focal field can be synthesized using the near-field pattern of the feed array. Although the result shows that the resulting gain of the reflector is about 1.5 dB lower than that of the conjugate field matching method, the average PA efficiency is improved by 39% (i.e., an improvement of radiation power efficiency from 6% to 28%).

B. AI for Antenna Arrays

In [A10], Nielsen *et al.* considered active phased arrays for 5G and 6G radios and proposed a DNN to perform a fault analysis. The DNN is tailored to classify different faults by extracting features hidden in the in-phase and quadrature components of the baseband signals. The validation of the method is performed on a commercial active phased array that operates at 28 GHz. The method achieves a 99% accuracy in single element failure detection and 80% accuracy for multiple-element fault detection.

In [A11], Wu *et al.* proposed an effective ML-assisted array synthesis method based on the active base element modeling. Specifically, the proposed model considers the effects of mutual coupling between each antenna element and the surrounding medium. Four practical design tasks are investigated to demonstrate the effectiveness and robustness of the proposed approach. The result shows that the proposed ML-assisted array synthesis method can offer a great design freedom, array performance, and design efficiency and cooperate with various optimization methods.

In [A12], Zhang *et al.* studied the pattern synthesis of a conformal phased array antenna by using a deep deterministic policy gradient algorithm, which is a typical deep reinforcement learning algorithm that has a strong fitting ability for high-dimensional continuous nonlinear problems. Such a property is exploited to design a conformal heterogeneous phased array antenna on the surface of an arbitrarily complex 3-D object, which is capable of performing fast and full solid angle beam-steering.

In [A13], Oliveri *et al.* focused on the application of ML to expedite the analyses of reflectarrays. Leveraging on the replacement of a unit cell with its digital twin to reduce the computational cost, the article extends digital twins to a wider set of reflectarray problems and derives the appropriate ML method by comparing different learning strategies and training approaches.

The contribution by Zhang *et al.* [A14] proposes a cognitive antenna array connected with a deep reinforcement learning model to quickly adapt to the complex electromagnetic environment. The platform contains a vector network analyzer and a microprogrammed control unit to observe and adjust the antenna array. The vector network analyzer feeds the signal for the phased array antenna through the power divider and transfers the measured gain to the host computer for the invocation of the deep reinforcement learning algorithm, whereas the microprogrammed control unit controls digital phase shifters to change the phase of each antenna element when receiving the command of phase distribution adjustment from the deep reinforcement learning model. The result shows a good agreement between the simulated and measured radiation patterns. The algorithm is also exploited in the design of a conformal phased array antenna, demonstrating the feasibility of auto-adjustment for different beam angles.

C. AI for Metasurfaces

In [A15], Naseri *et al.* combined ML with an optimization approach to obtain a design strategy for nonuniform bianisotropic metasurfaces. After a quite detailed bibliographic analysis, the contribution characterizes the main constraints to the device's parameters and then shifts to the proposed model, which divides the design into macroscopic and microscopic problems. A combination of ML and optimization techniques is first exploited to obtain the optimum macroscopic surface parameters. Then, the particle swarm optimization integrated with the DNN is employed to determine the microscopic properties. The contribution concludes with a set of realistic design scenarios which are tackled with the new technique, showing its practical impact.

In [A16], Wei *et al.* presented a design strategy for metasurfaces based on deep learning enhanced by equivalent circuit theory. The contribution starts with an analysis of the advantages and disadvantages of design strategies in literature and then delineates a different and promising approach. The core of the paper focuses on the definition and analyses of the new design idea, the role of circuit theory models and their use in an overall optimization scheme. A set of application examples is presented in detail with a special focus on frequency selective surfaces with different filtering properties.

In [A17], Zhu *et al.* proposed a Fourier subspace-based deep learning method for the inverse design of frequency selective surfaces. Data generated using the numerical simulation is first exploited to train the ANN model, and the trained ANN model is then used for the inverse design of dual-band frequency selective surfaces. The result shows that the ANN model can have a higher accuracy and computational efficiency when compared to the GA and the quasi-Newton method.

D. AI for Computational Electromagnetics

In [A18], Yin *et al.* proposed a cascaded neural network to solve volume integral equations for 3-D electromagnetic scattering from lossless dielectric objects. The proposed approach combines ML with the knowledge of the underlying physics of wave scattering to obtain a better performance than a pure black-box ML method. The paper discusses the advantages and limitations of general learning approaches for solving electromagnetic scattering problems involving dielectric scatterers.

In [A19], Xiang *et al.* applied the adaptive ANNs (AANNs) based on the physics locations of observation cells to rapidly predict the expansion coefficients of sub-entire-domain basis functions on interior, edge, and corner cells. This task is generally time-consuming due to the consideration of the mutual coupling between all the elements. However, by involving the AANNs, the mutual coupling among all the elements can be accounted into the neural networks without the construction of the mutual coupling matrix, and the expansion coefficients of sub-entire-domain basis functions can be obtained rapidly. This model may have a good generalization ability to analyze scattering problems of periodic structures out of the training dataset.

In [A20], Zhou *et al.* deal with multiphysics modeling of microwave filters enhanced via deep hybrid neural networks. The complexity intrinsic in multiphysics multiparametric models is tackled with an ad hoc strategy described in the core sections of the contributions. Special attention is devoted to showing the impact of the multiphysics approach when compared to single-physics strategies. This is also evident in the rich set of examples showing the applicability of the new scheme to a vast set of scenarios.

In [A21], Bhardwaj and Gaire focused on the solution of partial differential equations using neural networks. The paper, after an analysis of the previous work in the field, presents its main method applied to a second-order differential equation. The contribution then focuses on the possibility of doing transferred learning and applying the optimized data within one given differential framework to a different one. The work concludes with numerical experiments and with an insightful discussion of the obtained results.

E. AI for Other Applications

In [A22], Friedrichs *et al.* dealt with the use of ML approaches within the framework of "angle-of-arrival" estimation. After a literature review, the contribution presents in detail the general application setting, focusing in particular on the experimental configuration and model of the to-be-received signal. The paper then discusses the specific ML strategy that will be used together with the characterization of the training generation. The contribution ends with extensive numerical results where all proposed approaches are validated in quite relevant scenarios.

In [A23], Cil *et al.* employed a computationally heavy empirical approach and ML-based approach to design an optimal matching medium to be placed between an antenna and biological tissues. The ML model can predict the optimal matching medium permittivity and thickness for different targeted tissues (muscle, brain, and fat) and application scenarios. ML-based optimization methodologies are expected to be beneficial for antennas used in many biomedical and biological applications.

In [24], Xiao *et al.* proposed a method based on an ANN for the resonant-mode recognition of dielectric resonator antennas. The input vector of the ANN model consists of the information on electric fields, resonant frequencies, and geometric configurations of the dielectric resonator antenna. The ANN model can classify the resonant features and predict the dominant resonant mode of the antenna, with a 96.74% accuracy. Noticeably, although the accuracy can be increased by the CNN model, the execution time is considerably increased when compared to the ANN model.

In [A25], Wang *et al.* proposed a deep learning method to identify the inertia characteristics, such as the precession frequency, precession angle, spin frequency, and inertia ratio, of a cone-shaped space target based on time-varying scattering fields. To achieve this, a micro-Doppler spectrogram dataset is first constructed by time–frequency analysis with numerical simulation accelerated with a multistatic method and point scattering model, and experimental tests. The dataset is then compressed through singular value decomposition to reduce the training time in ML. The accuracy of identification is improved with the interaction loss function and feed-forward denoising CNNs.

III. Conclusion and Acknowledgment

Motivated by the emerging developments and some successful applications of ML and AI in antennas and electromagnetics, we have put together a collection of papers written by some of the active research groups, covering a wide range of topics, including optimal design of antennas and electromagnetic structures, array synthesis, numerical modeling and ML algorithms with data-driven techniques. We hope that these articles and the successes reported therein could serve to address the concerns of many of us in the antennas and propagation community as to why ML and data-driven design techniques have received remarkable attention over the past few years. We believe that ML and data-driven design and optimization will have a profound impact across many fields of antennas and propagation. Despite the intensive research during the past few years and many successful applications, research on AI and ML for antennas and electromagnetics is still in an early exploratory stage. Much remains to be done to make them highly useful and powerful tools for complicated real-world engineering applications. The objectives of this special issue are to review the current research activities, present novel and original ideas, share success stories and lessons learned, inspire further research on this important subject, and enrich the knowledge of the readers and researchers in this rapidly emerging field of study.

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Francesco Andriulli, Professor
Department of Electronics and Telecommunications
Politecnico di Torino
10129 Turin, Italy
e-mail: francesco.andriulli@polito.it

Pai-Yen Chen, Associate Professor
Department of Electrical and Computer Engineering
University of Illinois Chicago
Chicago, IL 60607 USA
e-mail: pychen@uic.edu

Danilo Erricolo, Professor
Department of Electrical and Computer Engineering
University of Illinois Chicago
Chicago, IL 60607 USA
e-mail: derric1@uic.edu

Jian-Ming Jin, Professor
Department of Electrical and Computer Engineering
University of Illinois Urbana–Champaign
Urbana, IL 61801 USA
e-mail: j-jin1@illinois.edu

References

[1] Z. Bayraktar, D. E. Anagnostou, S. K. Goudos, S. D. Campbell, D. H. Werner, and A. Massa, "Guest editorial: Special cluster on machine learning applications in electromagnetics, antennas, and propagation," *IEEE Antennas Wireless Propag. Lett.*, vol. 18, no. 11, pp. 2220–2224, Nov. 2019, doi: 10.1109/LAWP.2019.2945426.

[2] D. Erricolo *et al.*, "Machine learning in electromagnetics: A review and some perspectives for future research," in *Proc. Int. Conf. Electromagn. Adv. Appl. (ICEAA)*, 2019, pp. 1377–1380, doi: 10.1109/ICEAA.2019.8879110.

[3] R. Haupt and P. Rocca, "Artificial intelligence in electromagnetics [guest editorial]," *IEEE Antennas Propag. Mag.*, vol. 63, no. 3, p. 14, Jun. 2021, doi: 10.1109/MAP.2021.3069181.

[4] S. K. Goudos, D. E. Anagnostou, Z. Bayraktar, S. D. Campbell, P. Rocca, and D. H. Werner, "Guest editorial: Special section on computational intelligence in antennas and propagation: Emerging trends and applications," *IEEE Open J. Antennas Propag.*, vol. 2, pp. 224–229, 2021, doi: 10.1109/OJAP.2021.3057997.

[5] S. D. Campbell, R. P. Jenkins, P. J. O'Connor, and D. Werner, "The explosion of artificial intelligence in antennas and propagation: How deep learning is advancing our state of the art," *IEEE Antennas Propag. Mag.*, vol. 63, no. 3, pp. 16–27, Jun. 2021, doi: 10.1109/MAP.2020.3021433.

[6] F. Zardi, P. Nayeri, P. Rocca, and R. Haupt, "Artificial intelligence for adaptive and reconfigurable antenna arrays: A review," *IEEE Antennas Propag. Mag.*, vol. 63, no. 3, pp. 28–38, Jun. 2021, doi: 10.1109/MAP.2020.3036097.

[7] Q. Wu, W. Chen, C. Yu, H. Wang, and W. Hong, "Multilayer machine learning-assisted optimization-based robust design and its applications to antennas and array," *IEEE Trans. Antennas Propag.*, vol. 69, no. 9, pp. 6052–6057, Sep. 2021, doi: 10.1109/TAP.2021.3069491.

[8] D. R. Prado, J. A. Lopez-Fernandez, M. Arrebola, and G. Goussetis, "Support vector regression to accelerate design and crosspolar optimization of shaped-beam reflectarray antennas for space applications," *IEEE Trans. Antennas Propag.*, vol. 67, no. 3, pp. 1659–1668, Mar. 2019, doi: 10.1109/TAP.2018.2889029.

[9] S. Li, Z. Liu, S. Fu, Y. Wang, and F. Xu, "Intelligent beamforming via physics-inspired neural networks on programmable metasurface," *IEEE Trans. Antennas Propag.*, vol. 70, no. 6, pp. 4589–4599, Jun. 2022, doi: 10.1109/TAP.2022.3140891.

[10] Z. Ma, K. Xu, R. Song, C. Wang, and X. Cheng, "Learning-based fast electromagnetic scattering solver through generative adversarial network," *IEEE Trans. Antennas Propag.*, vol. 69, no. 4, pp. 2194–2208, Apr. 2021, doi: 10.1109/TAP.2020.3026447.

[11] Z. Wei and X. Chen, "Physics-inspired convolutional neural network for solving full-wave inverse scattering problems," *IEEE Trans. Antennas Propag.*, vol. 67, no. 9, pp. 6138–6148, Sep. 2019, doi: 10.1109/TAP.2019.2922779.

[12] M. Li *et al.*, "Machine learning in electromagnetics with applications to biomedical imaging: A review," *IEEE Antennas Propag. Mag.*, vol. 63, no. 3, pp. 39–51, Jun. 2021, doi: 10.1109/MAP.2020.3043469.

[13] A. Al-Saffar, A. Zamani, A. Stancombe, and A. Abbosh, "Operational learning-based boundary estimation in electromagnetic medical imaging," *IEEE Trans. Antennas Propag.*, vol. 70, no. 3, pp. 2234–2245, Mar. 2022, doi: 10.1109/TAP.2021.3111516.

[14] W. Shao and Y. Du, "Microwave imaging by deep learning network: Feasibility and training method," *IEEE Trans. Antennas Propag.*, vol. 68, no. 7, pp. 5626–5635, Jul. 2020, doi: 10.1109/TAP.2020.2978952.

APPENDIX: RELATED ARTICLES

[A1] W. T. Li, H. S. Tang, C. Cui, Y. Q. Hei, and X. W. Shi, "Efficient online data-driven enhanced-XGBoost method for antenna optimization," *IEEE Trans. Antennas Propag.*, vol. 70, no. 7, pp. 4953–4964, Jul. 2022.

[A2] D. Shi, C. Lian, K. Cui, Y. Chen, and X. Liu, "An intelligent antenna synthesis method based on machine learning," *IEEE Trans. Antennas Propag.*, vol. 70, no. 7, pp. 4965–4976, Jul. 2022.

[A3] K. Fu, X. Cai, B. Yuan, Y. Yang, and X. Yao, "An efficient surrogate assisted particle swarm optimization for antenna synthesis," *IEEE Trans. Antennas Propag.*, vol. 70, no. 7, pp. 4977–4984, Jul. 2022.

[A4] W. Chen, Q. Wu, C. Yu, H. Wang, and W. Hong, "Multibranch machine learning-assisted optimization and its application to antenna design," *IEEE Trans. Antennas Propag.*, vol. 70, no. 7, pp. 4985–4996, Jul. 2022.

[A5] Y. Sharma, X. Chen, J. Wu, Q. Zhou, H. H. Zhang, and H. Xin, "Machine learning methods-based modeling and optimization of 3-D-printed dielectrics around monopole antenna," *IEEE Trans. Antennas Propag.*, vol. 70, no. 7, pp. 4997–5006, Jul. 2022.

[A6] Y.-F. Liu, L. Peng, and W. Shao, "An efficient knowledge-based artificial neural network for the design of circularly polarized 3D-printed lens antenna," *IEEE Trans. Antennas Propag.*, vol. 70, no. 7, pp. 5007–5014, Jul. 2022.

[A7] Z. Z. Stankovic, D. I. Olcan, N. S. Doncov, and B. M. Kolundzija, "Consensus deep neural networks for antenna design and optimization," *IEEE Trans. Antennas Propag.*, vol. 70, no. 7, pp. 5015–5023, Jul. 2022.

[A8] P. Liu, L. Chen, and Z. N. Chen, "Prior-knowledge-guided deep-learning-enabled synthesis for broadband and large phase-shift range metacells in metalens antenna," *IEEE Trans. Antennas Propag.*, vol. 70, no. 7, pp. 5024–5034, Jul. 2022.

[A9] L. W. Mou, Y. J. Cheng, Y. F. Wu, M. H. Zhao, and H. N. Yang, "Design for array-fed beam-scanning reflector antennas with maximum radiated power efficiency based on near-field pattern synthesis by support vector machine," *IEEE Trans. Antennas Propag.*, vol. 70, no. 7, pp. 5035–5043, Jul. 2022.

[A10] M. H. Nielsen *et al.*, "Robust and efficient fault diagnosis of mm-wave active phased arrays using baseband signal," *IEEE Trans. Antennas Propag.*, vol. 70, no. 7, pp. 5044–5053, Jul. 2022.

[A11] Q. Wu, W. Chen, C. Yu, H. Wang, and W. Hong, "Machine learning-assisted array synthesis using active base element modeling," *IEEE Trans. Antennas Propag.*, vol. 70, no. 7, pp. 5054–5065, Jul. 2022.

[A12] B. Zhang *et al.*, "Ultra-wide-scanning conformal heterogeneous phased array antenna based on deep deterministic policy gradient algorithm," *IEEE Trans. Antennas Propag.*, vol. 70, no. 7, pp. 5066–5077, Jul. 2022.

[A13] G. Oliveri, M. Salucci, and A. Massa, "Towards efficient reflectarray digital twins—An EM-driven machine learning perspective," *IEEE Trans. Antennas Propag.*, vol. 70, no. 7, pp. 5078–5093, Jul. 2022.

[A14] B. Zhang, C. Jin, K. Cao, Q. Lv, and R. Mittra, "Cognitive conformal antenna array exploiting deep reinforcement learning method," *IEEE Trans. Antennas Propag.*, vol. 70, no. 7, pp. 5094–5104, Jul. 2022.

[A15] P. Naseri, S. Pearson, Z. Wang, and S. V. Hum, "A combined machine-learning/optimization-based approach for inverse design of nonuniform bianisotropic metasurfaces," *IEEE Trans. Antennas Propag.*, vol. 70, no. 7, pp. 5105–5119, Jul. 2022.

[A16] Z. Wei *et al.*, "Equivalent circuit theory-assisted deep learning for accelerated generative design of metasurfaces," *IEEE Trans. Antennas Propag.*, vol. 70, no. 7, pp. 5120–5129, Jul. 2022.

[A17] E. Zhu, Z. Wei, X. X. Xu, and W.-Y. Yin, "Fourier subspace-based deep learning method for inverse design of frequency selective surface," *IEEE Trans. Antennas Propag.*, vol. 70, no. 7, pp. 5130–5143, Jul. 2022.

[A18] T. Yin, C.-F. Wang, K. Xu, Y. Zhou, Y. Zhong, and X. Chen, "Electric flux density learning method for solving three-dimensional electromagnetic scattering problems," *IEEE Trans. Antennas Propag.*, vol. 70, no. 7, pp. 5144–5155, Jul. 2022.

[A19] W. Xiang, Z. Zhang, W. Zheng, J. Li, W. Yang, and W. Lu, "Rapid sub-entire-domain basis functions method based on adaptive artificial neural networks," *IEEE Trans. Antennas Propag.*, vol. 70, no. 7, pp. 5156–5164, Jul. 2022.

[A20] Y. Zhou, J. Xie, Q. Ren, H. Zhang, and Q. H. Liu, "Fast multi-physics simulation of microwave filters via deep hybrid neural network," *IEEE Trans. Antennas Propag.*, vol. 70, no. 7, pp. 5165–5178, Jul. 2022.

[A21] S. Bhardwaj and P. Gaire, "Data-free solution of electromagnetic PDEs using neural networks and extension to transfer learning," *IEEE Trans. Antennas Propag.*, vol. 70, no. 7, pp. 5179–5188, Jul. 2022.

[A22] G. R. Friedrichs, M. A. Elmansouri, and D. S. Filipovic, "A compact machine learning architecture for wideband amplitude-only direction finding," *IEEE Trans. Antennas Propag.*, vol. 70, no. 7, pp. 5189–5198, Jul. 2022.

[A23] E. Cil, C. Cadir, O. A. Kati, H. B. Yilmaz, and S. Dumanli, "Machine learning-based matching medium design for implant communications," *IEEE Trans. Antennas Propag.*, vol. 70, no. 7, pp. 5199–5208, Jul. 2022.

[A24] Y. Xiao, K. W. Leung, K. Lu, and C. S. Leung, "Mode recognition of rectangular dielectric resonator antenna using artificial neural network," *IEEE Trans. Antennas Propag.*, vol. 70, no. 7, pp. 5209–5216, Jul. 2022.

[A25] S. Wang *et al.*, "Cone-shaped space target inertia characteristics identification by deep learning with compressed dataset," *IEEE Trans. Antennas Propag.*, vol. 70, no. 7, pp. 5217–5226, Jul. 2022.