Guest Editorial
Artificial Intelligence in Radio Propagation for Communications

I. Introduction

THE era of wireless communications began at the turn of the 20th century, when Guglielmo Marconi used electromagnetic waves to transmit telegraph signals from ships to stations onshore [1]. To understand how radio signals propagate is critical for wireless communication system design. With the development of wireless communications, much effort has been made to characterize radio propagation in different frequency bands and physical environments. Radio propagation and wireless channel modeling are essential for communication system simulation, channel emulator design, wireless system planning and optimization, and the development of regulations and standards in wireless communications [2], [3].

Recently, the rapid growth in wireless data traffic is pushing against the boundary of wireless communication system performance. The beyond 5th generation (B5G) and 6th generation (6G) communication systems are expected to provide higher data rates, better coverage in various scenarios, lower latency, higher spectrum efficiency, as well as to support multiple frequency bands [4]–[6]. Particularly, providing reliable wireless coverage in various scenarios with different radio propagation characteristics is challenging for future communication system design. As expectations for the performance and reliability of B5G and 6G wireless systems expand, radio propagation and wireless channel modeling will continue to play a vital role in system design, evaluation, and deployment. Moreover, since radio propagation in different scenarios and frequency bands usually show different characteristics [7]–[16], a massive amount of research is needed in radio propagation characterization and modeling.

Radio propagation and channel characterization have been evolving over the years. Characterizations based on propagation mechanisms and approximations to Maxwell's equations or related laws of physics are usually considered as deterministic approaches. These models need to be validated with measurements and are useful for system deployments. Characterizations based on statistical descriptions of the channel responses are usually considered as statistical approaches, being mainly based on channel measurements taken over multiple representative spatial/temporal/spectral samples in a given environment (e.g., urban, rural, and indoor office). Combining the deterministic and stochastic approaches, geometry-based stochastic modeling has been developed to better characterize radio propagation channels. This approach utilizes greatly simplified ray tracing as well as measurement data for parameterization and validation [17], [18]. However, since 5G and beyond communication systems generally have larger bandwidths, more antenna elements, and higher mobility than conventional systems, large amounts of propagation data would still be needed [19]–[22]. Collecting and analyzing such large amounts of data for various communication scenarios present an imminent challenge for radio propagation characterization. Furthermore, future wireless communications will require robust intelligent algorithms to accurately predict radio propagation signals for different services in different scenarios.

In the present era of big data where data mining and data analysis technologies are effective tools for system evaluation and design, the applications of artificial intelligence (AI) in wireless communications are receiving a lot of attention [23], [24]. AI provides new and innovative solutions for the complex problem of communication system design. It is a powerful tool with many potential applications to enhance wireless communications. Radio propagation characterization and wireless channel modeling also benefit tremendously in this era. Specifically, AI has shown great ability in regression/prediction, clustering, tracking, and optimization, which are naturally suitable for the processing of radio propagation data. For example, clustering algorithms in machine learning (ML) are widely used for propagation channel feature extraction [25]–[28], and the resulting cluster-based propagation channel models are popular in both academia and industry. New learning-based approaches for radio propagation signal prediction, which usually employ neural networks (NNs) or deep learning (DL) algorithms, are also receiving a lot of attention in communication system design and performance evaluation [29], [30]. Many data mining techniques have been used for analyzing radio propagation data such as expectation maximization and support vector machines [31]–[34]. AI has also been widely used for communication scenario identification based on radio propagation characteristics [35]–[38]. Therefore, AI techniques have become a promising toolbox for the investigation of radio propagation in wireless communications.

The objective of this Special Issue is to showcase a unified vision for the applications of AI in radio propagation for communications and other relevant aspects. More specifically, the initial announcement encouraged emphasis in, but not limited to, the following areas: novel AI or AI-enabled techniques for radio propagation characterization and analysis; AI-enabled data analysis and parameter extractions of wireless channels;

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clustering analysis for radio channel characterization and modeling; AI-enabled channel modeling and communication system simulation; AI algorithm design in radio propagation for the applications in communications. All submitted papers went through a rigorous peer-review process, and 16 papers were eventually accepted covering a broad range of topics on AI in radio propagation for communications.

II. Main Contributions of the Papers in This Special Issue

The Special Issue begins with a two-part invited paper [A1], [A2] by Huang *et al.* which provides a comprehensive overview of AI-enabled radio propagation for communications. The first part of the overview focuses on channel parameter estimation and characterization as well as antenna-channel optimization, whereas scenario identification and channel modeling/prediction are investigated in the second part. Some results from early studies in the corresponding fields are demonstrated. Moreover, the pros and cons of the typical AI methods used in radio propagation related work are compared and analyzed. The future challenges of AI/ML-based channel data processing techniques are discussed as well.

In [A3], Seretis and Sarris present an overview of recent developments in the modeling of radio wave propagation based on ML algorithms. It is pointed out that the input and output specification and the architecture of the model are the main challenges associated with ML-driven propagation models. Relevant works are discussed. Emphasis is given to presenting the prospects and open problems in this promising and rapidly evolving area.

In [A4], Bharti *et al.* propose a likelihood-free calibration method for channel models using approximate Bayesian computation. The method is based on the maximum mean discrepancy, and it has the advantage of returning an entire posterior distribution on the value of the parameters, rather than a simple point estimate. The performance of the proposed method is evaluated by fitting two different stochastic channel models, namely the Saleh-Valenzuela model and the propagation graph model, to both simulated and measured data. The proposed method is able to estimate the parameters of both the models accurately in simulations, as well as when applied to 60 GHz indoor measurement data.

In [A5], Bai *et al.* propose an atmospheric data-driven Q-band satellite channel model using two artificial neural networks (ANNs), i.e., multilayer perceptron and long short-term memory (LSTM), to estimate real-time channel attenuation. Seven atmospheric parameters for modeling satellite channel attenuation are selected by the least absolute shrinkage and selection operator algorithm. The accuracy performance of multilayer perceptron- and LSTM-based channel models, such as absolute errors and mean-squared errors, are discussed and analyzed. The complexity parameters such as training time, loading time, and estimation time, are investigated. It is found that the estimated channel attenuation well aligns with the measured channel attenuation.

In [A6], Du *et al.* propose adaptive kernel-power-density (AKPD) and support vector machine-assisted AKPD (SVM-AKPD) algorithms for propagation channel clustering. First, a new distance-based metric is proposed to calculate an adaptive-K for each multipath component (MPC). Furthermore, the SVM is applied in clustering by the full partition of MPCs' feature space to overcome the limitation of the AKPD. Finally, the performance of the proposed AKPD and SVM-AKPD algorithms are validated with measured and simulated channels data, respectively, at the millimeter-wave (mm-wave) band. Both numerical simulations and experimental validation results are provided to demonstrate the effectiveness and robustness of the proposed algorithms. The proposed algorithms enable applications with no prior knowledge about the clusters, such as the number of clusters and their initial locations. It also does not need to adjust cluster parameters manually and can be implemented for cluster-based channel modeling with fairly low complexity.

In [A7], Zhou *et al.* investigate MPC clustering based on ML and analyze the cluster characteristics in typical high-speed railway (HSR) scenarios. A variational Bayesian Gaussian mixture model-based algorithm is used to achieve the space-time clustering of MPCs. A density-based validity index is proposed for evaluating clustering performance, and the proposed validity index improves the traditional index by considering the intracluster density, which can be calculated according to the Graham scanning method and Green's formula. In addition to synthetic datasets, realistic MPCs datasets collected in an HSR obstructed viaduct scenario are used for performance evaluation. Based on the clustering results in the measured scenario, static cluster characteristics, including cluster number, intercluster and intracluster delay spreads and angle spreads, and dynamic cluster characteristics are extracted and analyzed. These results will be useful for cluster-based channel modeling in future HSR mobile communication systems.

In [A8], Wang *et al.* use ML to develop a long-term prediction method of the usable working frequency for high-frequency wireless communication. The refined mapping model of the maximum usable frequency propagation factor for one hop on the F2 layer (of the ionosphere) is reconstructed by using the statistical ML method. Then, new mapping models of conversion factors of optimum working frequency and the highest probable frequency are proposed by using the fine-grained solar activity parameters and the coupling with two geomagnetic activity parameters. Compared with the International Telecommunication Union (ITU) recommended model, the root-mean-square errors of the maximum usable frequency, optimum working frequency, and highest probable frequency are reduced by 1.18 MHZ, 1.64 MHz, and 1.06 MHz, and the accuracies are improved by 10.89%, 15.47%, and 9.10%, respectively. The proposed model can achieve intelligent frequency planning for high-frequency communication.

In [A9], Zhang *et al.* propose a framework of ML-assisted mm-wave channel modeling, in which the statistical models are leveraged for inter-cluster-level channel characterization and the propagation properties within each kind of cluster are predicted using a hybrid physics-based and data-driven approach. In particular, with a focus on the mm-wave through-vegetation-scattering effect, a set of dedicated directional channel measurements and ray-tracing simulations are performed in an identical vegetated street canyon environment at 28 GHz for the performance evaluation of the proposed approach. Moreover, the training results and model validation in different environments show that, compared with the physical-statistical model, the proposed hybrid model, which adds the environment features to the ANN as inputs, has higher prediction accuracy and better generalization ability in terms of the site-specific through-vegetation cluster parameters, such as vegetation attenuation, delay spread, and angular spread.

In [A10], Chen *et al.* propose a general framework of Mahalanobis-distance metric for MPC clustering in MIMO channel analysis, without user-specified parameters. Remarkably, the popular multipath component distance is proven to be a special case of the proposed distance metric framework. Furthermore, two ML algorithms, namely, weak-supervised Mahalanobis metric for clustering and supervised large margin nearest neighbor, are introduced to learn the distance metric. To evaluate the effectiveness, a modified channel model is proposed based on the Third Generation Partnership Project (3GPP) spatial channel model to generate clustered MPCs with delay and angular information since the original 3GPP spatial channel model is incapable to evaluate clustering quality. Experiment results show that the proposed distance metric can significantly improve the clustering quality of existing clustering algorithms, while the learning phase requires considerably limited efforts in labeling MPCs.

In [A11], Zhao *et al.* propose a semi-deterministic mm-wave dynamic channel modeling approach based on the optimal neural network (ONN) principle. The ONNs are radial basis function NNs trained with optimal variance parameters and are applied to predict large-scale channel parameters. Based on the ONNs' predicted large-scale parameters and simplified propagation environment including the layout of the transmitter, receiver, and major scatterers, the proposed channel modeling approach can generate accurate dynamic channel parameters. The proposed approach is validated by the channel data measured at a high-voltage substation. Large-scale parameters, MPC distributions, and power delay profiles are validated. The proposed approach is demonstrated to be an accurate, fast, and robust channel modeling method.

In [A12], Gupta *et al.* propose an ML-based urban canyon path loss prediction model based on extensive 28 GHz measurements, where street clutters are modeled via a light detection and ranging point cloud dataset and buildings by a mesh-grid building dataset. The paper extracts expert knowledge-driven street clutter features from the point cloud and aggressively compresses the 3-D building information using a convolutional autoencoder. Using a new street-by-street training and testing procedure to improve generalizability, the proposed model using both clutter and building features is found to achieve a root-mean-squared-error prediction error of (4.8 ± 1.1) dB compared to (10.6 ± 4.4) dB and (6.5 ± 2.0) dB for 3GPP line of sight and slope-intercept prediction, respectively. By only using the four most influential clutter features, the root-mean-squared-error of (5.5 ± 1.1) dB is achieved.

In [A13], Seretis *et al.* present generalizable models for indoor propagation that can predict received signal strengths within new geometries, beyond the training set of the model, for transmitters and receivers of multiple positions, and for new frequencies. It is shown that a convolutional NN can learn the physics of indoor radiowave propagation from ray-tracing solutions of a small set of training geometries so that it can eventually deal with substantially different geometries. The article emphasizes the role of exploiting physical insights in the training of the network, by defining input parameters and cost functions that assist the network in efficiently learning basic and complex propagation mechanisms.

In [A14], Cazzella *et al.* design a DL-based low-rank channel estimation method to infer MIMO channel eigenmodes in vehicular urban settings, starting from a single least squares channel estimate and without needing vehicle's position information. Numerical results show that the proposed method attains comparable mean-squared-error performance as the position-based low-rank estimation. Moreover, the article shows that the proposed model can be trained on a reference scenario and be effectively transferred to urban contexts with different space-time channel features, providing comparable mean-squared-error performance without an explicit transfer learning procedure. This result eases the deployment in arbitrary dense urban scenarios.

In [A15], Bakirtzis *et al.* present an efficient ML-based radio propagation modeling framework for indoor environments. Specifically, this paper demonstrates how a convolutional encoder-decoder can be trained to replicate the results of a ray-tracer, by encoding physics-based information of an indoor environment, such as the permittivity of the walls, and decode it as the path loss heatmap for an environment of interest. The model is trained over multiple indoor geometries and frequency bands, and it can eventually predict the path loss for unknown indoor geometries and frequency bands within a few milliseconds. In addition, it illustrates how the concept of transfer learning can be leveraged to calibrate the model by adjusting its pre-estimate weights, allowing it to make predictions that are consistent with measurement data.

In [A16], Liu *et al.* present an ML scheme based on the geographic feature to predict received signal strength. It elaborately selects four features closely related to received signal strength from the easily acquired geographic dataset and designs low-cost methods for computing them. Experiments are executed in the large-scale outdoor scenario at 3.5 GHz for a 5G network where the real received signal strength data is collected by the field measurement in an urban environment. Four state-of-the-art ML algorithms are adopted for the proposed scheme and algorithm accuracy is compared with the Stanford University interim model, ECC-33 model, and the ray-tracing method. The experiment results show the validity of the extracted features. Besides, the proposed scheme performs well in its model accuracy and computational efficiency compared with the existing methods.

III. Conclusion and Acknowledgment

Despite the promising progress reported in this Special Issue, many long-standing problems remain unsolved in the application of AI in radio propagation. For example, this

Special Issue includes many concrete proposals on AI-based channel parameter estimation and characterization. However, for time-varying non-stationary channels, the proposed algorithms and frameworks still need to be improved significantly. Supervised AI-based clustering and tracking methods are worth receiving more attention in the future, especially considering the phenomenal increase in both the amount of collected channel measurement data and the available computing power. Likewise, AI-based radio propagation prediction requires further enhancements. In the present Special Issue, several AI-based solutions have appeared that cleverly use deep learning networks to learn the data pattern and predict propagation characteristics. Nevertheless, some known propagation properties, e.g., channel sparsity in high-frequency propagation, are not well considered during the AI network design. Besides, the interaction of radio propagation and other B5G/6G technologies are worth deeper AI-based investigations, e.g., how to use AI-based radio propagation technologies in the integration of sensing and communications, how to control propagation signals using reconfigurable intelligent surfaces with AI support, etc. Not surprisingly, the field of AI in radio propagation continues to attract new researchers worldwide.

By compiling these articles, we have found AI in radio propagation to be a fascinating topic with many new challenges, which we hope will enrich the knowledge of readers and researchers. We sincerely thank all the authors and reviewers for their contributions, and we especially thank the Editor-in-Chief and Staff Members of the IEEE TRANSACTIONS ON ANTENNAS AND PROPAGATION for their constant support over the entire process from the proposal to the final publication.

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Appendix: Related Articles

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