Generative-Adversarial-Network-Based Wireless Channel Modeling: Challenges and Opportunities

Yang Yang, Yang Li, Wuxiong Zhang, Fei Qin, Pengcheng Zhu, and Cheng-Xiang Wang

Traditional channel modeling methods, such as ray-tracing and geometry-based stochastic channel models, require in-depth domain-specific knowledge and technical expertise in radio signal propagations across electromagnetic fields. To avoid these difficulties and complexities, the authors propose a novel generative adversarial network framework to address the problem of autonomous wireless channel modeling without complex theoretical analysis or data processing.

Abstract

In modern wireless communication systems, wireless channel modeling has always been a fundamental task in system design and performance optimization. Traditional channel modeling methods, such as ray-tracing and geometry-based stochastic channel models, require in-depth domain-specific knowledge and technical expertise in radio signal propagations across electromagnetic fields. To avoid these difficulties and complexities, a novel generative adversarial network (GAN) framework is proposed for the first time to address the problem of autonomous wireless channel modeling without complex theoretical analysis or data processing. Specifically, the GAN is trained by raw measurement data to reach the Nash equilibrium of a MinMax game between a channel data generator and a channel data discriminator. Once this process converges, the resulting channel data generator is extracted as the target channel model for a specific application scenario. To demonstrate, the distribution of a typical additive white Gaussian noise channel is successfully approximated by using the proposed GAN-based channel modeling framework, thus verifying its good performance and effectiveness.

Introduction

Wireless channel modeling has always been a fundamental task for theoretical research and practical implementation of modern wireless communication systems. The upcoming fifth generation (5G) wireless communication systems will support machine-to-machine, device-to-device, and vehicle-to-vehicle communications, and will have more application scenarios for vertical industries, such as enhanced mobile broadband (eMBB), massive machine type communications (mMTC), and ultra-reliable and low-latency communications (URLLC) [1, 2]. Accurate channel models help us understand the exact physical impacts of different wireless channels on transmitted radio signals, which is the crucial knowledge enabling us to design and deploy effective and feasible communication technologies for different propagation channels in real application environments.

In the literature, tremendous efforts have been devoted to developing effective methods for accurate channel modeling. In [3], a principal component analysis (PCA)-based method was proposed for characterizing and modeling multiple-iInput multiple-output (MIMO) channels. This approach can extract some hidden features and structures from measured channel data, which are used to effectively reconstruct the amplitude and phase of channel impulse response (CIR) together with detailed information of measurement environments and antenna configurations. In [4], the spatial correlation and channel capacity of 2D and 3D MIMO channel models were compared. The results illustrated the importance and challenges of channel modeling in performance evaluation of 3D MIMO systems. In [5], some clustering techniques and big data algorithms were analyzed and applied to clustered channel modeling with massive measurement data. These traditional channel modeling methods require in-depth domain-specific knowledge and technical expertise in radio signal propagation across electromagnetic fields. The corresponding models are usually:

- Very complex with many parameters
- Not applicable to predict statistical properties of wireless channels
- Not flexible to be transferred for other communication environments

To address those constraints and limitations of traditional channel modeling methods, neural networks and machine learning techniques are considered as potential universal solutions for different 5G application scenarios and communication environments. Specifically, neural networks are very effective for approximate arbitrary functions and hidden features. Machine learning algorithms have been developed to predict wireless channel characteristics [6], and to optimize system capacity and service coverage [7] in massive MIMO systems. In addition, thanks to the latest developments of fog/edge computing technologies [8-9], more intelligent and sophisticated methods and algorithms can be executed effectively in local or neighboring environments with very relevant measurement data, system parameters, and network resources. In this article, based on the concept of the generative adversarial network (GAN) [10, 11], we propose and analyze an intelligent universal channel modeling method, which uses two artificial neural networks (ANNs)

Digital Object Identifier: 10.1109/MCOM.2019.1800635

Yang Yang (corresponding author) is with ShanghaiTech University; Yang Li is with ShanghaiTech University and Shanghai Research Center for Wireless Communications; Wuxiong Zhang is with Shanghai Research Center for Wireless Communications and Chinese Academy of Sciences; Fei Qin is with the University of Chinese Academy of Sciences; Pengcheng Zhu and Cheng-Xiang Wang are with Southeast University.

as the channel data generator and the channel data discriminator in the GAN-based framework for autonomous wireless channel modeling without any domain-specific knowledge or technical expertise. In particular, the GAN is trained by channel measurement data to reach the Nash equilibrium of a MinMax game between the generator and the discriminator. Once this process converges, the resulting channel data generator is the target channel model learned from the raw measurement data in a specific application scenario. As an example, the distribution of a typical additive white Gaussian noise (AWGN) channel is successfully approximated by using our proposed GAN-based channel modeling framework, which completely avoids the theoretical analysis and complex processing of raw measurement data in traditional channel modeling methods.

The rest of this article is organized as follows. Several traditional channel modeling methods are reviewed. The GAN-based channel modeling framework is proposed and analyzed, followed by a discussion of key technical challenges. A typical AWGN channel is used to evaluate the performance and effectiveness of the proposed GAN-based channel modeling framework. Finally, we conclude this article.

Traditional Channel Modeling Methods

Stored Channel Impulse Responses: One of the realistic channel modeling methods is to use a sophisticated channel sounder [12] to measure a variety of channel parameters, including direction of departure (DoD), direction of arrival (DoA), time delay, Doppler shift, and so on. These key parameters are then combined to form the CIRs, which will play a key role in wireless network design and performance optimization. Usually, channel measurement campaigns are time-consuming and limited to a few dedicated measurement environments, which is expensive and not flexible.

Deterministic Channel Models: Deterministic wireless channel models are based on the channel parameters calculated from the communication environments and propagation law of electromagnetic waves. Ray-tracing techniques are the most popular deterministic channel modeling methods, where all waves are modeled as rays that behave as in geometrical optics. Refinements are used at the modeling phase (approximation to diffraction, diffuse scattering, etc.). In this way, ray-tracing techniques can simulate reflection, diffraction, refraction, and scattering by using the information of exact communication environments. Hence, the parameters of almost every propagation path can be derived theoretically to obtain the channel model.

Stochastic Channel Models: The geometry-based stochastic channel model (GSCM) [13] is a representative stochastic channel modeling method. A GSCM is obtained by using the fundamental laws of reflection, diffraction, and scattering of electromagnetic waves in an environment of many scatterers under a certain distribution. GSCMs have been widely used due to their convenience for theoretical analysis and mathematical tractability. Besides, GSCMs can reproduce the stochastic characteristics of different categories of wireless channels over time, frequency, and space. GSCMs can also be described by some selected parameters, such as angle of departure (AoD) and angle of arrival (AoA). These parameters are randomly chosen according to a particular distribution. However, GSCMs are very complex when a large number of random parameters are used. In such cases, GSCMs are especially difficult and time-consuming for link-level simulations.

Normally, channel models are developed by either simulations or measurements. Obviously, simulation-based methods are usually cheaper than measurement-based methods, but the performance of the former approach is greatly constrained by many unrealistic assumptions and neglected subtle details about the type, size, and location of different scatterers in specific communications environments. The latter approach is often used to capture and analyze wireless channel characteristics, as well as to evaluate and validate various simulation results. This is because measurement results contain all the details in real communication environments, and they are generated on site in real time, and thus of great value to professional researchers and engineers. Generally speaking, channel measurement campaigns need a carefully configured channel sounder for different channel types (i.e., static and dynamic channels). Other physical phenomena that should be considered are:

- Nonlinear transfer functions of active devices
- Frequency-dependent antenna patterns
- Coupling effects among adjacent antenna elements

Typically, a channel measurement campaign has two phases, the development phase and the production phase. The first phase is mainly to evaluate the performance of the channel sounder and the corresponding models. Some important system parameters and data collection protocols are then carefully tuned and optimized. The second phase is mainly to capture massive raw measurement data. This large volume of data is fully analyzed to derive key channel parameters, and their distributions and correlations. Finally, the resulting channel models are represented by CIRs or probability density functions (PDFs) according to the actual requirements in the design and analysis of wireless communications systems.

Typically, a channel measurement campaign has two phases, the development phase and the production phase. The first phase is mainly to evaluate the performance of the channel sounder and the corresponding models. Some important system parameters and data collection protocols are then carefully tuned and optimized. The second phase is mainly to capture massive raw measurement data.

GAN-Based Channel Modeling Framework

As discussed earlier, accurate channel measurements for massive MIMO systems in dynamic application scenarios are very difficult, time-consuming, and expensive. It is even harder to fully analyze big measurement data and quickly estimate a comprehensive set of various channel parameters, which require sophisticated scientific knowledge, in-depth technical know-how, and extensive practical experiences in wireless communications and electromagnetic fields. Different from complex traditional approaches, this article proposes a GAN-based channel modeling framework, as shown in Fig. 1, in order to minimize the need for domain-specific knowledge and technical expertise in wireless communications and signal propagation across electromagnetic fields.

Channel Real Samples: This is the database of raw measurement data obtained from prac-

The channel data generator and discriminator in this GAN-based framework are trained concurrently in order to minimize the loss. In the continuous battle between these two important units, the discriminator becomes smarter and more captious, while the generator produces better and better fake samples that are more and more identical to the real ones.

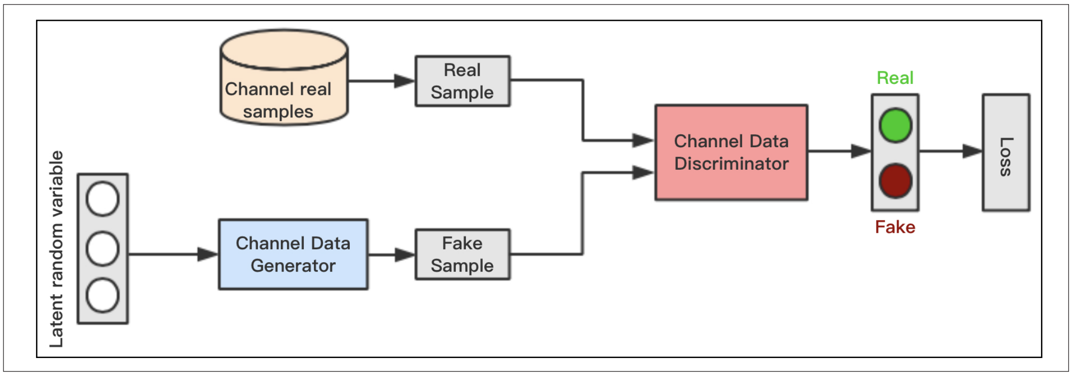

Figure 1. The GAN-based wireless channel modeling framework.

tical experiments and measurement campaigns. As specified in [12], a parallel channel sounder is developed and used for MIMO channel measurements in different application scenarios. Massive raw data is shared at a free-access website for 5G research communities (www.wise.sh). The samples in this big database contain a variety of MIMO channel characteristics in real measurement environments and at different frequency bands.

Channel Data Generator: By using latent random variables, this unit tries its best to generate fake samples as real as possible, compared to the real samples collected from wireless channels. It directly learns the distribution of CIRs and can capture the key characteristics of a target wireless channel. A channel data generator is usually represented by an ANN, which has powerful ability in function approximation and is trained to generate fake channel samples that minimize the probability of the channel data discriminator's correct answer.

Channel Data Discriminator: By using another ANN, this unit is trained to distinguish between the real samples (from a target wireless channel) and the fake samples (from the channel data generator). It aims to maximize the probability of assigning correct labels to these examples. Together with the channel data generator, which tries to minimize the probability that the channel data discriminator makes a right decision through adversarial training, both units jointly accomplish the complicated channel modeling task through a MinMax game, which has an optimization objective of minimum loss.

The channel data generator and discriminator in this GAN-based framework are concurrently trained in order to minimize the loss. In the continuous battle between these two important units, the discriminator becomes smarter and more captious, while the generator produces better and better fake samples that are more and more identical to the real ones. This training process stops when the discriminator can no longer distinguish fake samples or real samples (i.e., two error probabilities are equally 50 percent). Finally, the equilibrium between the generator and the discriminator is achieved. The channel data generator is then extracted as the target channel model, which is purely learned from this GAN-based framework without any domain-specific knowledge or technical expertise.

Technical Challenges

The proposed GAN-based channel modeling framework simplifies the process of wireless channel modeling. However, several technical challenges need to be addressed.

Channel Data Acquisition: As discussed above, we take advantage of the aforementioned channel sounder to collect real-world channel data for adversarial training between the channel data generator and the channel data discriminator. However, this approach has several limitations:

- In practical channel measurement campaigns, raw data collection and pre-processing are time-consuming and expensive. If any errors are found in the measured data, it takes the same amount of effort, cost, and time to conduct all the measurements again.
- Due to the physical limitations in some communication environments, the corresponding channel measurement campaigns may have stringent requirements on the size, weight, and power supply of a channel sounder.
- When channel measurement requirements are very specific and sophisticated, it is more challenging and expensive to conduct channel measurement campaigns with higher accuracy.

Convergence: Unlike the relatively simpler learning problems such as classification have a clear concept of "right" and "wrong," training a generative model like GAN is far more complicated because it is often unclear how "good" a sample from the model is, although it indeed has a loss function to watch. This is because GANs are in fact two models competing with each other, so they will both try to achieve the lowest loss while augmenting the other model's loss. Moreover, GANs are usually trained by using gradient descent algorithms, which are good at identifying the low value of a loss function, rather than the Nash equilibrium of a non-convex game. Thus, these algorithms may not converge when the Nash equilibrium is required for training the GANs. Another difficulty in training GANs is that the generator finds one sample that fools the discriminator, and then keeps on generating simple variations of that sample without learning to generate more distinct samples. This situation may occur when a particular gradient descent algorithm gets stuck in a local minimum.

Recently, feature matching is being considered as a promising technique for encouraging the convergence of training GANs [11]. It solves the instability problem of GANs by setting a new goal for the generator to avoid overtraining the corresponding discriminator. On one hand, the generator is required to generate data following the statistics of actual data. On the other hand, the discriminator is trained to identify the statistics that are worth matching with, instead of simply maximizing the output of it. Specifically, after training, the generator can match the average value of the features on an intermediate layer of the discriminator. This is an ideal choice for the generator, since the discriminator is trained to identify the most discriminative features between actual data and the fake samples generated by a model. Figure 2 shows the cumulative distribution function (CDF) of the number of iterations for the GAN framework to converge when it is trained with or without feature matching. It is obvious that training the GAN with feature matching (green dashed curve) converges much faster than the latter (red solid curve).

Model Generalization: The final channel data generator is extracted as the target channel model from the converged GAN through adversarial training with the raw measurement data. However, the learned channel model can only characterize the distribution of key channel parameters in specific measurement campaigns and communication environments. This target channel model cannot be generalized to other communication environments with different signal propagation conditions. For example, an indoor channel model with rich multipath parameters is not suitable for an outdoor urban environment.

Since the GAN-based channel model (i.e., the channel data generator) is essentially an ANN, a transfer learning strategy [14] can be applied to generalize the channel model for different communication scenarios. In practice, we can derive a GAN-based channel model from a very large channel measurement dataset, which takes a variety of communication scenarios into consideration during the measurement campaigns, and then use this trained model as an initialization for the particular scenario of interest.

Explainability: Deep learning techniques have been very successfully applied to solve computer vision problems. However, it is widely questioned why they work and what the hidden layers have learned. To find the answers, researchers have visualized the hidden layers of an image recognition neural network to learn the mechanism by which they work. Similarly, we could know more about what the hidden layers of the channel data generator have learned by comparing the outputs of hidden layers with parameters of propagation effects of the parametric channel modeling methods.

Performance Evaluation

To evaluate the performance and effectiveness of the proposed GAN-based channel modeling framework, an AWGN channel is chosen in the simulation, and a large amount of real samples are prepared for the training process.

Key parameters

As shown in Fig. 1, the proposed GAN framework consists of a channel data generator and a channel data discriminator. The architectures and key parameters of the generator and discriminator are given in Table 1. The learning rate is to control the speed of stochastic gradient descent, which is a typical training algorithm of neural networks. The decay rate is used to control the learning rate during the training process. We use rectified linear units (ReLUs) as the activation function, leveraging its ability to avoid gradient vanishing. The minibatch size is set as 32 for the channel data generator and channel data discriminator. Moreover, the discriminator has 3 hidden layers, and each of them has 100 neurons, more than the corresponding numbers set in the channel data generator. This is because the discriminator needs stronger computational power to distinguish real samples from fake samples.

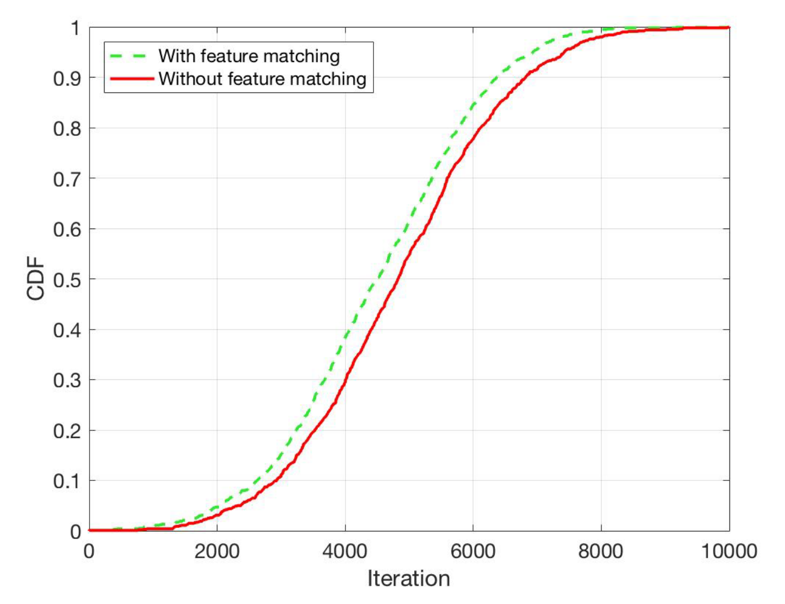

Figure 2. The CDF of the number of iterations that the GAN model takes to converge.

Numerical Results

For an AWGN channel, the envelope of the channel response is modeled to have a Gaussian distribution. In this sense, the effectiveness of our learned channel model is verified by comparing its PDF to that of the AWGN channel. We train the GAN framework with the real samples generated from a Gaussian distribution with a mean of 4 and a standard deviation of 0.5. The channel data generator is extracted as an approximation of the real AWGN channel when the GAN finally converges. Ideally, it converges when the channel data discriminator fails to distinguish real samples from fake samples, that is, the probabilities that the channel data discriminator assigns correct labels to both real and fake samples are equally 50 percent.

In the beginning of training process, the generator produces a very different distribution from the real data, as shown in Fig. 3. However, it finally learns to approximate the true channel PDF quite closely before converging to a more compact distribution focused on the mean of the real distribution. After training, the two distributions are presented in Fig. 4. It seems that the generated distribution is much narrower than the real distribution. An intuitive explanation is that the channel data discriminator is looking at individual samples from the real channel data and from the channel data generator. If the generator happens

	Channel data generator	Channel data discriminator
Learning rate	0.001	0.010
Learning rate decay	1.0×10^{-5}	1.0×10^{-4}
Activation function	ReLU	ReLU
Minibatch size	32	32
Number of hidden layers	2	3
Neuron number of each hidden layer	50	100

Table 1. Key parameters of the channel data generator and channel data discriminator.

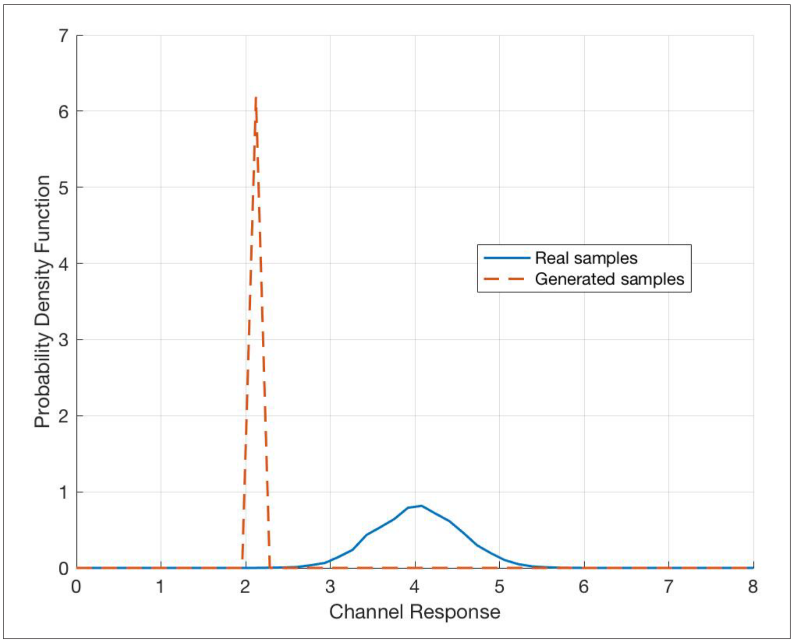

Figure 3. The PDFs of the real channel response samples and the generated channel response samples in the beginning of the training process.

to produce the mean value of the real data, this specific sample is quite likely to fool the discriminator. Sometimes, the generator collapses to a parameter setting and results in a very narrow distribution of points, which is one of the main failure modes of GANs [11].

Fortunately, minibatch discrimination allows the discriminator to analyze multiple samples at once during the training process [11]. Minibatch discrimination improves sample diversity where the discriminator is able to look at an entire batch of samples in order to decide whether they come from the generator or a real measurement dataset. Finally, Fig. 5 compares the PDFs of the real channel samples and the generated channel samples. It demonstrates that the proposed GAN-based framework can effectively offer a fairly good approximation of the real channel model, without any domain-specific knowledge or technical expertise in wireless communications and data analysis.

Lessons and Opportunities

This research presents a novel approach to applying GANs to addressing the challenging problem of autonomous wireless channel modeling, without domain-specific knowledge, complex theoretical analysis, or sophisticated data processing. Through the process of design and experimentation with this GAN-based framework, we have learned some valuable lessons and identified a few potential opportunities for fellow researchers:

- The architecture of GAN should not be too deep. The neural network of the discriminator should have more hidden layers, thus being more powerful in computation capability than the generator.
- It is difficult to properly train the GAN and ensure its convergence. The trick is to pay much more attention to the configuration of the loss function, as well as the training process of the discriminator.
- As to the hyper-parameters in Table 1, a small learning rate is always a safe choice for training the GAN. Besides, the learning rate decay technique is quite helpful during the training process.
- While the minibatch discrimination technique is used, it is better to keep a relatively small batch size in order to make sure the training process will converge.
- ReLU is a desirable activation function that can reduce the likelihood of the gradient vanishing and the gradient's non-saturation, thus greatly accelerating the convergence of Stochastic Gradient Descent (SGD).
- SGD is the preferred optimization algorithm for the channel data discriminator, while the Adam algorithm [15] is good for the channel data generator.
- Last but not least, this proposed GAN-based channel modeling framework is scalable and can be extended to large-scale application scenarios such as MIMO by utilizing MIMO inputs and outputs. In order to accommodate this extension, the structures of the input layer and output layer should be changed according to the MIMO configuration of the neural network model.

Conclusion

In this article, a GAN-based wireless channel modeling framework has been proposed and analyzed. Different from traditional methods using complex theoretical analysis and sophisticated data processing to derive key channel parameters from real measurement data, our new method does not require any domain-specific knowledge or technical expertise, and can obtain the target channel model by directly learning from massive raw channel data with a GAN, which aims to achieve the Nash equilibrium of a MinMax game between a channel data generator and a channel data discriminator. Taking an AWGN channel as a simple example, the PDF of generated channel samples has been compared with that of the real channel data. The results have demonstrated that the proposed GAN-based channel modeling framework can offer a fairly good approximation of the real wireless channel. Our future work includes more experiments with real MIMO channel datasets generated from previous measurement campaigns (www.wise.sh).

Acknowledgments

This work was supported in part by the National Natural Science Foundation of China (NSFC) under Grant 61571004, the Science and Technology Commission of Shanghai Municipality (STCSM) under Grant 18511106500, the CAS Scientific Instrument Developing Project under Grant YJKYYQ20170074, and the EU H2020 RISE TESTBED Project under Grant 734325.

References

[1] C.-X. Wang *et al.*, "Cellular Architecture and Key Technologies for 5G Wireless Communication Networks," *IEEE Commun. Mag.*, vol. 52, no. 2, Feb. 2014, pp. 122–30.

[2] Y. Yang *et al.*, *5G Wireless Systems: Simulation and Evaluation Techniques*, Springer, 2018.

[3] X. Ma *et al.*, "A PCA-Based Modelling Method for Wireless MIMO Channel," *Proc. 2017 IEEE Conf. Computer Commun. Wksps.*, Atlanta, GA, 2017, pp. 874–79.

[4] Y. Yu *et al.*, "3D vs. 2D Channel Models: Spatial Correlation and Channel Capacity Comparison and Analysis," *Proc. ICC 2017*, Paris, France, 2017, pp. 1–7.

[5] R. He *et al.*, "Clustering Enabled Wireless Channel Modeling Using Big Data Algorithms," *IEEE Commun. Mag.*, no. 5, May 2018, pp. 177–83.

[6] L. Bai *et al.*, "Predicting Wireless mmWave Massive MIMO Channel Characteristics Using Machine Learning Algorithms," *Wireless Commun. and Mobile Computing*, vol. 2018, Aug. 2018.

[7] Y. Yang *et al.*, "DECCO: Deep-Learning Enabled Coverage and Capacity Optimization for Massive MIMO Systems," *IEEE Access*, vol. 6, no. 1, Dec. 2018, pp. 23,361–71.

[8] S. Zhao *et al.*, "FEMOS: Fog-Enabled Multi-tier Operations Scheduling in Dynamic Wireless Networks," *IEEE Internet of Things J.*, vol. 5, no. 2, Apr. 2018, pp. 1169–83.

[9] Y. Yang *et al.*, "DEBTS: Delay Energy Balanced Task Scheduling in Homogeneous Fog Networks," *IEEE Internet of Things J.*, vol. 5, no. 3, June 2018, pp. 2094–2106.

[10] I. Goodfellow *et al.*, "Generative Adversarial Nets," *Proc. 2014 Conf. Neural Info. Processing Systems*, Montreal, Canada, Dec. 2014, pp. 2672–80.

[11] T. Salimans *et al.*, "Improved Techniques for Training GANs," *Proc. 2016 Conf. Neural Info. Processing Systems*, Barcelona, Spain, Dec. 2016, pp. 2234–42.

[12] Y. Yang *et al.*, "Parallel Channel Sounder for MIMO Channel Measurements," *IEEE Wireless Commun.*, vol. 25, no. 5, Oct. 2018, pp. 16–22.

[13] M. Zhu, G. Eriksson, and F. Tufvesson, "The COST 2100 Channel Model: Parameterization and Validation Based on Outdoor MIMO Measurements at 300 MHz," *IEEE Trans. Wireless Commun.*, vol. 12, no. 2, Feb. 2013, pp. 888–97.

[14] S. J. Pan and Q. Yang, "A Survey on Transfer Learning," *IEEE Trans. Knowledge and Data Engineering*, vol. 22, no. 10, Oct. 2010, pp. 1345–59.

[15] D. P. Kingma and J. Ba, "Adam: A Method for Stochastic Optimization," *Proc. 3rd Int'l. Conf. Learning Representations*, San Diego, CA, Mar. 2015.

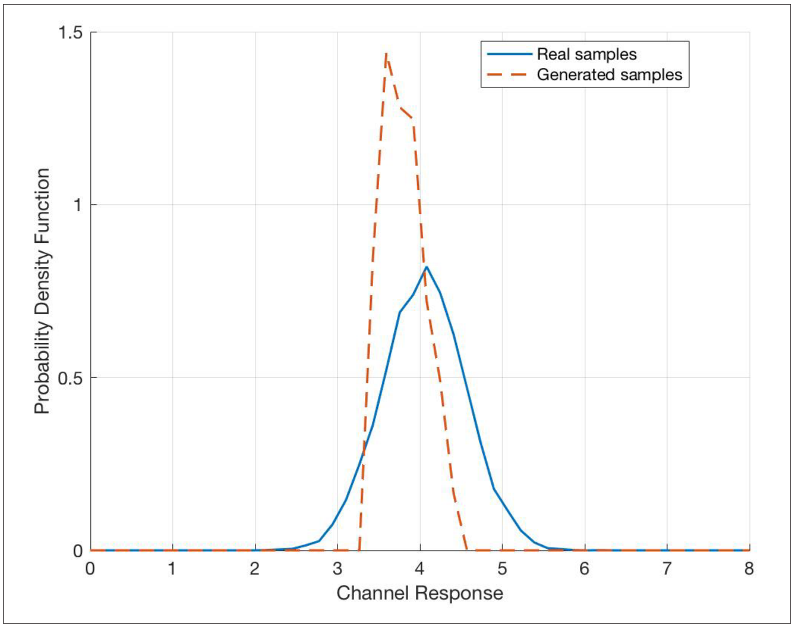

Figure 4. The PDFs of the real channel response samples and the generated channel response samples without minibatch discrimination.

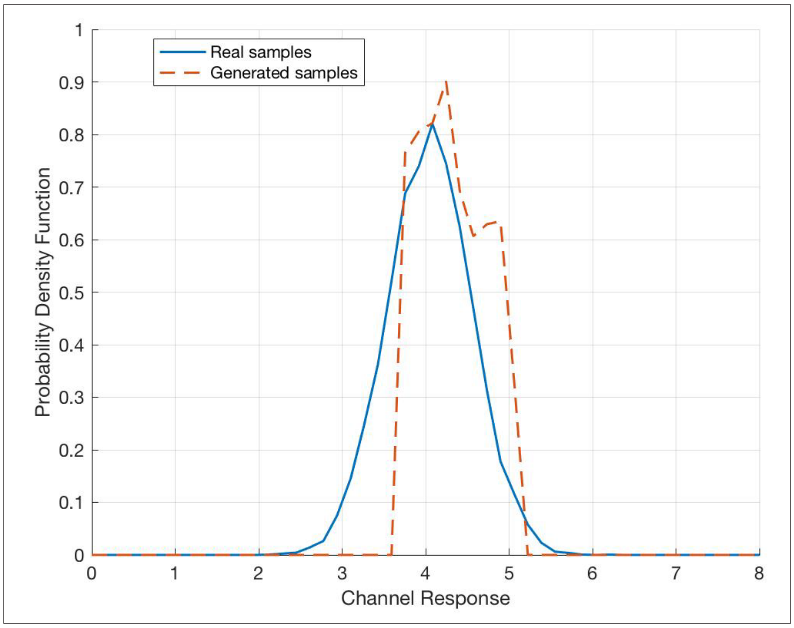

Figure 5. The PDF of the real channel response samples and the generated channel response samples with minibatch discrimination.

Biographies

YANG YANG [S'99, M'02, SM'10, F'18] (yangyang@shanghaitech.edu.cn) is a professor with the School of Information Science and Technology, ShanghaiTech University, China. He is the executive dean of School of Creativity and Art, and the co-director of Shanghai Institute of Fog Computing Technology (SHIFT). His research interests include wireless sensor networks, Internet of Things, fog computing, Open 5G, and advanced wireless testbeds. He has published more than 200 papers in these areas.

YANG LI (liyang@shanghaitech.edu.cn) received his Ph.D. degree with co-supervision from ShanghaiTech University and the University of the Chinese Academy of Sciences in 2018. He is now a research engineer at Huawei Technologies. His research interests include machine learning in the wireless domain, practical wireless systems implementation, and fog computing.

WUXIONG ZHANG (wuxiong.zhang@mail.sim.ac.cn) is an associate professor at SIMIT, Chinese Academy of Sciences. He received his Ph.D. degree from the University of the Chinese Academy of Sciences in 2013. His research interests include 5G mobile communications, vehicular networks, and heterogeneous networks. He has published more than 50 papers and submitted 11 technical patents.

FEI QIN (fqin1982@ucas.ac.cn) received his Ph.D. degree from University College London, United Kingdom, in 2012. He is an associate professor with the College of Electronic and Electrical Communication Engineering, University of the Chinese Academy of Sciences. His research interests include joint optimization methods of wireless networks and information systems for industrial applications.

PENGCHENG ZHU (p.zhu@seu.edu.cn) is an associate professor with the National Mobile Communications Research Laboratory, Southeast University, China. His research interests include distributed and large-scale MIMO, cellular architecture, and energy-efficient techniques for wireless communication networks.

CHENG-XIANG WANG [S'01, M'05, SM'08, F'17] (chxwang@seu.edu.cn) received his Ph.D. degree from Aalborg University, Denmark, in 2004. He joined Heriot-Watt University in 2005 and became a professor in 2011. In 2018, he joined Southeast University as a professor. He has co-authored two books, one book chapter, and over 340 papers in refereed journals and conference proceedings. His current research interests include wireless channel measurements/modeling and (B)5G wireless communication networks. He is a Fellow of the IET, is an IEEE Communications Society Distinguished Lecturer for 2019 and 2020, and was a Highly Cited Researcher recognized by Clarivate Analytics in 2017 and 2018.