# Guest Editorial Special Issue on Distributed Learning Over Wireless Edge Networks—Part II

Mingzhe Chen, *Member, IEEE*, Deniz Gündüz, *Senior Member, IEEE*, Kaibin Huang, *Fellow, IEEE*, Walid Saad, *Fellow, IEEE*, Mehdi Bennis, *Fellow, IEEE*, Aneta Vulgarakis Feljan, *Member, IEEE*, and H. Vincent Poor, *Life Fellow, IEEE*

THIS is Part II of a double-part special issue on distributed learning over wireless edge networks. This two-part special issue features papers dealing with two main research challenges: optimization of wireless network performance for efficient implementation of distributed learning in wireless networks, and distributed learning for solving communication problems and optimizing network performance. The accepted papers in this special issue have been grouped into three topics: 1) network optimization for federated learning (FL), 2) network optimization for other distributed learning methods, and 3) distributed reinforcement learning (RL) for wireless network optimization. In Part I (vol. 39, no. 12, Dec. 2021), the focus is on the first cluster (network optimization for FL). The focus of Part II is on the second and third clusters (network optimization for other distributed learning methods and RL for wireless network optimization). The readers are referred to Part I for an overview paper [A1] by the team of guest editors where a comprehensive study of how distributed learning can be efficiently deployed over wireless edge networks is provided. The contributions made by the papers in Part II are summarized as follows.

## I. Network Optimization for Distributed Optimization

In [A2], Saha *et al.* consider distributed optimization in a wireless network where communication between devices is hindered.

Mingzhe Chen and H. Vincent Poor are with the Department of Electrical and Computer Engineering, Princeton University, Princeton, NJ 08544 USA (e-mail: mingzhec@princeton.edu; poor@princeton.edu).

Deniz Gündüz is with the Department of Electrical and Electronic Engineering, Imperial College London, London SW7 2AZ, U.K. (e-mail: d.gunduz@imperial.ac.uk).

Kaibin Huang is with the Department of Electrical and Electronic Engineering, The University of Hong Kong, Hong Kong (e-mail: huangkb@eee.hku.hk).

Walid Saad is with the Wireless@VT, Bradley Department of Electrical and Computer Engineering, Virginia Tech, Blacksburg, VA 24060 USA (e-mail: walids@vt.edu).

Mehdi Bennis is with the Department of Communications Engineering, University of Oulu, 90014 Oulu, Finland (e-mail: mehdi.bennis@oulu.fi).

Aneta Vulgarakis Feljan is with Ericsson Research, 16483 Stockholm, Sweden (e-mail: aneta.vulgarakis@ericsson.com).

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In [A3], Tegin *et al.* use unequal error protection (UEP) codes to obtain an approximation to a matrix product arising in the distributed training to provide greater protection for those blocks with greater effect on the training performance. The authors characterize the performance of the proposed approach from a theoretical perspective by bounding the expected reconstruction error for matrices with uncorrelated entries.

In [A4], Van Huynh *et al.* jointly optimize computational coding and device scheduling to minimize the convergence time of distributed learning while considering the dynamics and uncertainty of wireless connections and edge devices. To solve this optimization problem, the authors reformulate the problem as a Markov decision process and then design a novel deep RL algorithm that employs the deep dueling neural network architecture to find a jointly optimal coding scheme and an optimal set of edge devices for different learning tasks without explicit information about the wireless environment and edge devices' straggling parameters.

In [A5], Ning *et al.* propose a gradient sparsification technique with a renovating mechanism for distributed edge learning. The authors also provide a theoretical convergence guarantee for the proposed algorithm with non-convex loss functions.

In [A6], Xu *et al.* study the impact of network topology construction on the peer-to-peer training performance.

## II. Network Optimization for Over-the-Air Computation Based Distributed Learning

In [A7], Paul *et al.* consider the deployment of FL over over-the-air computation (AirComp) based wireless networks. The authors propose a novel accelerated gradient-descent multiple access algorithm that uses momentum-based gradient signals over noisy fading multiple access channels to improve the FL convergence rate. The authors also analyze the convergence of the proposed scheme and establish a finite-sample bound of the errors for both convex and strongly convex loss functions with Lipschitz gradients.

In [A8], Lee *et al.* study schemes and lower bounds for distributed minimax estimation over a Gaussian multiple-access channel under squared error loss. First, the authors develop "analog" joint estimation-communication schemes that exploit the superposition property of the Gaussian multiple-access channel. Then, the authors derive information-theoretic lower bounds on the minimax risk of any estimation scheme that is restricted to communicate the samples over a given number of uses of the channel. In addition, the authors compare both achievability and lower bound results to previous "digital" lower bounds, where devices transmit errorless bits at the Shannon capacity of multiple-access channels.

In [A9], Liu and Simeone study distributed Bayesian learning in a wireless data center setting consisting of a central server and multiple distributed workers. In particular, the authors investigate the design of distributed one-shot Bayesian learning protocols via consensus Monte Carlo. Uncoded transmission is introduced not only as a way to implement AirComp but also as a mechanism to deploy channel-driven Monte Carlo sampling. Rather than treating channel noise as a nuisance to be mitigated, channel-driven sampling utilizes channel noise as an integral part of the Monte Carlo sampling process.

In [A10], Pu *et al.* propose an incremental learning framework within a 5th generation (5G) network architecture. In particular, the authors first formulate an online data scheduling problem to optimize the training cost while alleviating the data skew caused by the capacity heterogeneity of devices. To solve this problem, the authors use duality to separate the original problem into a series of time-independent per-slot problems and each per-slot problem can be separated into a data collection and a data training subproblem. Then, the authors treat these two subproblems in a skew-aware manner and propose optimal algorithms based on novel graph constructions to respectively solve them.

In [A11], Shi *et al.* design a proactive defense method for local model poisoning attacks. More specifically, the authors propose a federated anomaly analytics enhanced distributed learning algorithm, where the devices and the server collaboratively analyze anomalies. In the proposed algorithm, the server firstly detects all the uploaded local models and splits out the potentially malicious ones using a lightweight and unsupervised anomaly detection method based on support vector machine. Then, it verifies each potentially malicious local model with functional encryption. Finally, it removes the verified anomalies and aggregates the remaining local FL models to generate a global model.

## III. Network Optimization for Distributed Convolutional Neural Networks

In [A12], Cai *et al.* focus on accelerating the training of distributed convolutional neural networks (CNNs) at the network edge. The authors introduce a novel dynamic programming-based communication scheduler that dynamically decomposes each transmission procedure into several segments such that each device can simultaneously perform optimal layer-wise model transmission and computation.

## IV. Network Optimization for Multi-Split Machine Learning

In [A13], Wang *et al.* present a practical multi-split machine learning system tailored for 5G cellular networks. The authors first introduce the optimization problem whose goal is to minimize the total transmission and computation latency via finding an optimal machine learning model split decision. To solve the proposed problem, the authors reformulate this problem into a min-cost graph search and propose a distributed min-cost graph algorithm tailored for 5G networks. Through graph pruning and information aggregation, the designed algorithm can reduce the communication overhead among different devices.

## V. Reinforcement Learning for Network Optimization

In [A14], Wu *et al.* consider a resource allocation and offloading decision-making problem in a mobile edge computing (MEC) network where mobile devices may connect to different computational access points (CAPs) during different time slots. To solve this problem, the authors propose a robust distributed hierarchical online learning approach.

In [A15], Liu *et al.* study the deployment of FL in an AirComp-based network and propose a learning rate optimization scheme to reduce the FL model errors caused by fading channels.

In [A16], Zhang *et al.* propose a multi-agent double deep Q network-based approach to jointly optimize the beamforming vectors and power splitting ratio in multi-user multiple-input single-output simultaneous wireless information and power transfer-enabled heterogeneous networks.

In [A17], Zhang *et al.* propose a mobile edge computing-enabled virtual reality (VR) streaming system, where VR video viewport prediction and communication resource allocation are integrated to achieve efficient VR streaming. The authors first propose a federated averaging-based algorithm to learn the VR video viewing pattern in a distributed manner. Then, the dueling double deep recurrent Q-network is used to find an optimal resource allocation strategy for each VR user.

In [A18], Liu *et al.* study the use of MEC, reconfigurable intelligent surfaces (RISs), and terahertz (THz) technology to service VR users in an indoor scenario, by taking into account the uplink viewpoint prediction and position transmission, MEC rendering, and downlink transmission.

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## Appendix: Related Articles

[A1] M. Chen *et al.*, "Distributed learning in wireless networks: Recent progress and future challenges," *IEEE J. Sel. Areas Commun.*, early access, 2021.

[A2] R. Saha, S. Rini, M. Rao, and A. Goldsmith, "Decentralized optimization over noisy, rate-constrained networks: Achieving consensus by communicating differences," *IEEE J. Sel. Areas Commun.*, early access, Oct. 6, 2021, doi: 10.1109/JSAC.2021.3118428.

[A3] B. Tegin, E. E. Hernandez, S. Rini, and T. M. Duman, "Straggler mitigation through unequal error protection for distributed approximate matrix multiplication," 2021, *arXiv:2103.02928*. [Online]. Available: https://arxiv.org/abs/2103.02928

[A4] N. Van Huynh, D. T. Hoang, D. N. Nguyen, and E. Dutkiewicz, "Joint coding and scheduling optimization for distributed learning over wireless edge networks," 2021, *arXiv:2103.04303*. [Online]. Available: https://arxiv.org/abs/2103.04303

[A5] W. Ning *et al.*, "Following the correct direction: Renovating sparsified SGD towards global optimization in distributed edge learning," *IEEE J. Sel. Areas Commun.*, early access, Oct. 6, 2021, doi: 10.1109/JSAC.2021.3118396.

[A6] H. Xu, M. Chen, Z. Meng, Y. Xu, L. Wang, and C. Qiao, *Decentralized Machine Learning Through Experience-Driven Method in Edge Networks*.

[A7] R. Paul, Y. Friedman, and K. Cohen, "Accelerated gradient descent learning over multiple access fading channels," *IEEE J. Sel. Areas Commun.*, early access, Oct. 6, 2021, doi: 10.1109/JSAC.2021.3118410.

[A8] C.-Z. Lee, L. P. Barnes, and A. Özgür, "Over-the-air statistical estimation," *IEEE J. Sel. Areas Commun.*, early access, Oct. 7, 2021, doi: 10.1109/JSAC.2021.3118412.

[A9] D. Liu and O. Simeone, "Channel-driven Monte Carlo sampling for Bayesian distributed learning in wireless data centers," 2021, *arXiv:2103.01351*. [Online]. Available: https://arxiv.org/abs/2103.01351

[A10] L. Pu, X. Yuan, X. Xu, X. Chen, P. Zhou, and J. Xu, "Cost-efficient and skew-aware data scheduling for incremental learning in 5G networks," *IEEE J. Sel. Areas Commun.*, early access, Oct. 6, 2021, doi: 10.1109/JSAC.2021.3118430.

[A11] S. Shi, C. Hu, D. Wang, Y. Zhu, Y. Zhu, and Z. Han, "Federated anomaly analytics for local model poisoning attack," *IEEE J. Sel. Areas Commun.*, early access, Oct. 11, 2021, doi: 10.1109/JSAC.2021.3118347.

[A12] S. Cai *et al.*, "DynaComm: Accelerating distributed CNN training between edges and clouds through dynamic communication scheduling," 2021, *arXiv:2101.07968*. [Online]. Available: http://arxiv.org/abs/2101.07968

[A13] S. Wang, X. Zhang, H. Uchiyama, and H. Matsuda, "HiveMind: Towards cellular native machine learning model splitting," *IEEE J. Sel. Areas Commun.*, early access, Oct. 6, 2021, doi: 10.1109/JSAC.2021.3118403.

[A14] Y.-C. Wu, C. Lin, and T. Q. S. Quek, "A robust distributed hierarchical online learning approach for dynamic MEC networks," *IEEE J. Sel. Areas Commun.*, early access, Oct. 6, 2021, doi: 10.1109/JSAC.2021.3118342.

[A15] Y. Liu, X. Guan, Y. Peng, H. Chen, T. Ohtsuki, and Z. Han, "Blockchain based task offloading for edge computing on low-quality data via distributed learning in the Internet of energy," *IEEE J. Sel. Areas Commun.*, early access, Oct. 8, 2021, doi: 10.1109/JSAC.2021.3118417.

[A16] R. Zhang, K. Xiong, Y. Lu, B. Gao, P. Fan, and K. B. Letaief, *Joint Coordinated Beamforming and Power Splitting Ratio Optimization in MU-MISO SWIPT-Enabled HetNets: A Multi-Agent DDQN-Based Approach*.

[A17] R. Zhang, K. Xiong, Y. Lu, B. Gao, P. Fan, and K. B. Letaief, "Buffer-aware virtual reality video streaming with personalized and private viewport prediction," *IEEE J. Sel. Areas Commun.*, early access, Oct. 11, 2021, doi: 10.1109/JSAC.2021.3119144.

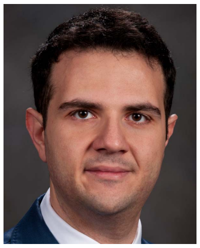
[A18] X. Liu, Y. Deng, C. Han, and M. Di Renzo, "Learning-based prediction, rendering and transmission for interactive virtual reality in RIS-assisted terahertz networks," *IEEE J. Sel. Areas Commun.*, early access, Oct. 8, 2021, doi: 10.1109/JSAC.2021.3118405.

**Mingzhe Chen** (Member, IEEE) received the Ph.D. degree from the Beijing University of Posts and Telecommunications, Beijing, China, in 2019. From 2016 to 2019, he was a Visiting Researcher at the Department of Electrical and Computer Engineering, Virginia Tech. He is currently a Post-Doctoral Research Associate with the Department of Electrical and Computer Engineering, Princeton University. His research interests include federated learning, reinforcement learning, virtual reality, unmanned aerial vehicles, and wireless networks. He was a recipient of the 2021 IEEE ComSoc Young Author Best Paper Award. He received three conference best paper awards at IEEE ICC in 2020, IEEE GLOBECOM in 2020, and IEEE WCNC in 2021. He currently serves as an Associate Editor of IEEE TRANSACTIONS ON GREEN COMMUNICATIONS AND NETWORKING and a Guest Editor for IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS (JSAC) Special Issue on "Distributed learning over wireless edge networks."

**Deniz Gündüz** (Senior Member, IEEE) received the B.S. degree in electrical and electronics engineering from METU, Turkey, in 2002, and the M.S. and Ph.D. degrees in electrical engineering from the NYU Tandon School of Engineering (formerly Polytechnic University) in 2004 and 2007, respectively.

After his Ph.D., he served as a Post-Doctoral Research Associate at Princeton University, as a Consulting Assistant Professor at Stanford University, and as a Research Associate at CTTC, Barcelona, Spain. In September 2012, he joined the Department of Electrical and Electronic Engineering, Imperial College London, U.K., where he is currently a Professor of information processing, and serves as the Deputy Head of the Intelligent Systems and Networks Group. He is also a part-time Faculty Member of the University of Modena and Reggio Emilia, Italy, and has held visiting positions at the University of Padova (2018–2020) and Princeton University (2009–2012). His research interests include the areas of communications and information theory, machine learning, and privacy. He was a recipient of the IEEE Communications Society—Communication Theory Technical Committee (CTTC) Early Achievement Award in 2017, a Starting Grant of the European Research Council (ERC) in 2016, and several best paper awards. He is a Distinguished Lecturer of the IEEE Information Theory Society (2020–2022). He is an Area Editor of the IEEE TRANSACTIONS ON INFORMATION THEORY, IEEE TRANSACTIONS ON COMMUNICATIONS, and the IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS (JSAC) Special Series on "Machine learning in communications and networks." He also serves as an Editor for the IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS.

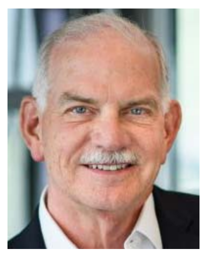
**Kaibin Huang** (Fellow, IEEE) received the B.Eng. and M.Eng. degrees in electrical engineering from the National University of Singapore and the Ph.D. degree from The University of Texas at Austin. He is currently an Associate Professor with the Department of Electrical and Electronic Engineering, The University of Hong Kong, Hong Kong. He received the IEEE Communication Society's 2021 Best Survey Paper, the 2019 Best Tutorial Paper, the 2019 Asia-Pacific Outstanding Paper, the 2015 Asia-Pacific Best Paper Award, and the best paper awards at IEEE GLOBECOM 2006 and IEEE/CIC ICCC 2018. He also received the Outstanding Teaching Award from Yonsei University, South Korea, in 2011. He has been named as a Highly Cited Researcher by the Clarivate Analytics in 2019 and 2020. He served as the Lead Chair for the Wireless Communications Symposium of IEEE GLOBECOM 2017 and the Communication Theory Symposium of IEEE GLOBECOM 2014, and the TPC Co-Chair for IEEE PIMRC 2017 and IEEE CTW 2013. He is also an Executive Editor of IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS, an Associate Editor of IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS, and an Area Editor of IEEE TRANSACTIONS ON GREEN COMMUNICATIONS AND NETWORKING. Previously, he served on the Editorial Board for IEEE WIRELESS COMMUNICATIONS LETTERS. He has guest edited special issues on IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS, IEEE JOURNAL OF SELECTED TOPICS IN SIGNAL PROCESSING, and *IEEE Communications Magazine*. He is also a Distinguished Lecturer of the IEEE Communications Society and the IEEE Vehicular Technology Society, and a Research Fellow of Hong Kong Research Grants Council.



**Walid Saad** (Fellow, IEEE) received the Ph.D. degree from the University of Oslo in 2010. He is currently a Professor with the Department of Electrical and Computer Engineering, Virginia Tech, where he leads the Network sciEnce, Wireless, and Security (NEWS) laboratory. His research interests include wireless networks, machine learning, game theory, security, unmanned aerial vehicles, cyber-physical systems, and network science. From 2015 to 2017, he was named the Stephen O. Lane Junior Faculty Fellow at Virginia Tech, and in 2017, he was a Faculty Fellow of the College of Engineering. He is an IEEE Distinguished Lecturer. He was also a recipient of the NSF CAREER Award in 2013, the AFOSR Summer Faculty Fellowship in 2014, and the Young Investigator Award from the Office of Naval Research (ONR) in 2015. He was the author/coauthor of ten conference best paper awards at WiOpt in 2009, ICIMP in 2010, IEEE WCNC in 2012, IEEE PIMRC in 2015, IEEE SmartGridComm in 2015, EuCNC in 2017, IEEE GLOBECOM in 2018, IFIP NTMS in 2019, IEEE ICC in 2020, and IEEE GLOBECOM in 2020. He was a recipient of the 2015 Fred W. Ellersick Prize from the IEEE Communications Society, the 2017 IEEE ComSoc Best Young Professional in Academia Award, the 2018 IEEE ComSoc Radio Communications Committee Early Achievement Award, and the 2019 IEEE ComSoc Communication Theory Technical Committee. He was also a coauthor of the 2019 IEEE Communications Society Young Author Best Paper and the 2021 IEEE Communications Society Young Author Best Paper. He received the Dean's Award for Research Excellence from Virginia Tech in 2019. He currently serves as an Editor for the IEEE TRANSACTIONS ON MOBILE COMPUTING, the IEEE TRANSACTIONS ON NETWORK SCIENCE AND ENGINEERING, and the IEEE TRANSACTIONS ON COGNITIVE COMMUNICATIONS AND NETWORKING. He is also the Editor-at-Large of the IEEE TRANSACTIONS ON COMMUNICATIONS.

**Mehdi Bennis** (Fellow, IEEE) is currently a Professor with the Centre for Wireless Communications, University of Oulu, Finland, an Academy of Finland Research Fellow, and the Head of the Intelligent Connectivity and Networks/Systems Group (ICON). He has published more than 200 research papers in international conferences, journals, and book chapters. His main research interests include radio resource management, heterogeneous networks, game theory, and distributed machine learning in 5G networks and beyond. He was a recipient of several prestigious awards, including the 2015 Fred W. Ellersick Prize from the IEEE Communications Society, the 2016 Best Tutorial Prize from the IEEE Communications Society, the 2017 EURASIP Best paper Award for the *Journal of Wireless Communications and Networking*, the all-University of Oulu Award for Research, the 2019 IEEE ComSoc Radio Communications Committee Early Achievement Award, and the 2020 Clarviate Highly Cited Researcher by the Web of Science. He is an Editor of IEEE TRANSACTIONS ON COMMUNICATIONS (TCOM) and the Specialty Chief Editor for data science for communications in the *Frontiers in Communications and Networks* journal.

**Aneta Vulgarakis Feljan**, (Member, IEEE) received the Ph.D. degree in computer science from Mälardalen University, Sweden, in 2012, focused on component-based modeling and formal analysis of real-time embedded systems. She is currently a Senior Research Manager in artificial intelligence at Ericsson Research. Before joining Ericsson Research, She was a Scientist at ABB Corporate Research. She is the coauthor of more than 40 refereed publications on software engineering and AI topics and a co-inventor of over 50 patent families. Her main research interests include AI-based cyber-physical systems and the combination of model-driven and data-driven AI. She is an editor, an organizer, and a program committee member in many top-ranked journals, conferences, and workshops, as well as a keynote speaker and a panelist on multiple events organized by industry and academia. Her paper "A Component Model for Control-Intensive Distributed Embedded Systems" has been awarded the ICSA 2018 Most Influential Paper Award.



**H. Vincent Poor** (Life Fellow, IEEE) received the Ph.D. degree in EECS from Princeton University in 1977. From 1977 to 1990, he was on the faculty of the University of Illinois at Urbana-Champaign. Since 1990, he has been on the faculty at Princeton, where he is currently the Michael Henry Strater University Professor. From 2006 to 2016, he served as the Dean of Princeton's School of Engineering and Applied Science. He has also held visiting appointments at several other universities, including most recently at Berkeley and Cambridge. His research interests are in the areas of information theory, machine learning, and network science, and their applications in wireless networks, energy systems, and related fields. Among his publications in these areas is the forthcoming book *Machine Learning and Wireless Communications* (Cambridge University Press). Dr. Poor is a member of the National Academy of Engineering and the National Academy of Sciences and is a foreign member of the Chinese Academy of Sciences, The Royal Society, and other national and international academies. He received the IEEE Alexander Graham Bell Medal in 2017.