The Korean Institute of Communications and Information Sciences

Available online at www.sciencedirect.com

ScienceDirect

ICT Express 8 (2022) 230–234

www.elsevier.com/locate/icte

An optimal location strategy for multiple drone base stations in massive MIMO[☆]

Manuel Eugenio Morocho-Cayamcela[a,1], Wansu Lim[b,*,1], Martin Maier[c,2]

[a] Yachay Tech University, School of Mathematical and Computational Sciences, Deep Learning for Autonomous Driving, Robotics, and Computer Vision Research Group (DeepARC), Hacienda San José, San Miguel de Urcuquí, Ecuador

[b] Department of Aeronautics, Mechanical and Electronic Convergence Engineering, Kumoh National Institute of Technology, Gumi, Gyeongsangbuk-do 39177, South Korea

[c] Optical Zeitgeist Laboratory, INRS, Montreal QC, H5A 1K6, Canada

Received 15 March 2021; received in revised form 11 May 2021; accepted 3 August 2021
Available online 25 August 2021

Abstract

The concept of drone base stations (DBSs) has been applied to reduce the distance of the wireless link between a macro base station and its active users under diverse scenarios in military communications, smart industries, and high-density networks, and to provide service in topologies with damaged infrastructure. In this paper, we address the optimal positioning of multiple DBSs in a multiple-input multiple-output wireless network setting. We present a low-complexity machine learning-based algorithm to optimize the location of the DBSs by minimizing the collective wireless received signal strength experienced by the active terminals. The proposed algorithm reduces the propagation loss in the system and provides a lower bit error rate when compared with the Euclidean cost benchmark.

Keywords: Disaster scenario; Massive MIMO; Path planning; Unmanned aerial vehicle; User association

1. Introduction

Unmanned aerial vehicles or *drones* offer unique advantages such as fast deployment and mobility. Consequently, they have considerable potential to enhance the quality of service (QoS) in multiple fields such as agriculture, industry, smart factories, military, and telecommunications [1]. One of the emerging use-cases of drones for 5G+ or 6G is their use as base stations (BSs) in the telecommunications industry to serve scenarios with an extremely high user-equipment (UE) density, extend wireless communication coverage, recover from damage in existing infrastructure, improve spectral efficiency by reducing the link distance, and increase the quality of experience in diversified services. Owing to the growth in the number of UEs, combined with high-mobility scenarios and new antenna technologies such as massive multiple-input multiple-output (MIMO), tracking the location and trajectory of drone BSs (DBSs) has become a renewed research area. Path planning of DBSs has become one of the most critical problems to be addressed in mission-critical operations and disaster response [2]. Conventional cell-selection in a fixed BS scenario is performed by selecting the BS according to the strongest received power. Fixed BS topologies have been proven to be non-optimal in regard to spectrum utilization [3]. Heterogeneous networks have assisted in the optimization of the spectrum by reducing the distance from the macro-cell BS (MBS) to its UE [4]. Nevertheless, further optimization of the spectrum with DBSs requires a minimization of the collective distance between the drone serving as the BS and its active UE [5–7]. Studies have been conducted to solve the location problem of single-antenna DBSs with mixed-integer non-linear programming (MINLP) techniques, which have proven to be highly complex [8]. Previous works have been conducted with the consideration of the minimization of a metric space

☆ This work was supported by the Ministry of SMEs and Start-ups, S. Korea (S2829065, S3010704), and by the National Research Foundation of Korea (2020R1A4A101777511).

* Corresponding author.
E-mail addresses: mmorocho@yachaytech.edu.ec (M.E. Morocho-Cayamcela), wansu.lim@kumoh.ac.kr (W. Lim), maier@emt.inrs.ca (M. Maier).

1 Member, IEEE.

2 Senior Member, IEEE.

Peer review under responsibility of The Korean Institute of Communications and Information Sciences (KICS).

https://doi.org/10.1016/j.icte.2021.08.010

2405-9595/

function in a d-dimensional Euclidean space $\mathbb{R}^d$ to solve the location problem of DBSs [9–13]. In a massive MIMO setting where the DBSs will be equipped with a considerable number of antennas, the investigation of the channel, the positioning of DBSs, and cell-selection problems are even more complex such that the implementation of MINLP solvers has a considerable impact on the network performance [14–17]. Although a metric space can be considered under certain applications, it has been proven that, due to the characteristics of radio propagation, the shortest distance between transceivers is not always optimal owing to obstructions between the transmitter and receiver antennas [18,19].

In this paper, we address the optimal positioning of multiple DBSs in a massive MIMO wireless network setting. First, we introduce the DBS massive MIMO wireless communication model and then present a low-complexity unsupervised machine-learning (ML)-based algorithm that iteratively selects the location of the DBSs according to the collective wireless channel propagation experienced by the active UEs, instead of the conventional metric space cost function. The proposed algorithm updates the location of the DBS, minimizing the channel propagation after every iteration. Furthermore, we analyze the bit error rate (BER) after each iteration, evaluate the impact of the number of DBSs in the network, and prove the convergence of our algorithm.

2. DBS trajectory selection in massive MIMO

This section introduces the massive MIMO communication model used in this study and the formulation of the proposed unsupervised DBS trajectory selection algorithm.

2.1. DBS massive MIMO system model

We consider a cellular massive MIMO system in which a total of L DBSs are equipped with an array of M antennas and serve K terminals simultaneously via spatial multiplexing. Let the gain between the kth terminal and the mth DBS antenna be represented as g_k^m. Assuming that the DBSs antennas are configured in a compact array, the wireless links between a given UE and all the DBS antennas are influenced by an equal large-scale fading coefficient β_k that depends on k, the aerial distance, and different small-scale fading h_k^m, but not on m. Hence, g_k^m can be expressed as

$$g_k^m = \sqrt{\beta_k} h_k^m, \quad k = 1, \ldots, K, \quad m = 1, \ldots, M. \tag{1}$$

The small-scale fading follows an independent Rayleigh distribution between the UEs and DBS antennas, such that $\{h_k^m\}$ are i.i.d. circularly symmetric Gaussian random variables with the mean $\mu = 0$ and the variance $\sigma^2 = 1$ (i.e., CN(0,1)). We let the channel gains between all the UEs and all the DBSs be represented by the matrix

$$\boldsymbol{G} = \begin{bmatrix} g_1^1 & \cdots & g_K^1 \\ \vdots & \ddots & \vdots \\ g_1^M & \cdots & g_K^M \end{bmatrix}. \tag{2}$$

In the uplink, the UEs simultaneously transmit the K signals $x_1, \ldots, x_K$, and the mth DBS antenna receives the signal

$$y_m = \sqrt{\rho_{ul}} \sum_{k=1}^{K} g_k^m x_k + w_m, \tag{3}$$

where ρ_{ul} is the uplink signal-to-noise ratio (SNR), and $w_m \sim$ CN(0,1) is the receiver noise, with $\{w_m\}$ uncorrelated across antennas. We constrain the transmit powers of the terminals individually as $\mathrm{E}\left\{|x_k|^2\right\} \leq 1$, where $\mathrm{E}\{\cdot\}$ is the averaging operator, and we consider that the transmitted signals have zero mean $\mathrm{E}\{x_k\} = 0$. Thus, according to (3), the M antennas in the DBS receive the vector $\boldsymbol{y} = [y_1, \ldots, y_M]^\top$, with $(\cdot)^\top$ as the transpose operator

$$\boldsymbol{y} = \sqrt{\rho_{ul}} \sum_{k=1}^{K} \boldsymbol{g}_k x_k + \boldsymbol{w} = \sqrt{\rho_{ul}} \boldsymbol{G}\boldsymbol{x} + \boldsymbol{w}, \tag{4}$$

with $\boldsymbol{x} = [x_1, \ldots, x_K]^\top$, $\boldsymbol{w} = [w_1, \ldots, w_M]^\top$, and $\boldsymbol{g}_k$ as the kth column of the matrix $\boldsymbol{G}$. In the downlink, the M DBS antennas send the M-vector $\boldsymbol{x}$, and through reciprocity, the kth UE receives

$$y_k = \sqrt{\rho_{dl}} \boldsymbol{g}_k^\top \boldsymbol{x} + w_k, \tag{5}$$

where ρ_{dl} is the downlink SNR and w_k is the noise. If we formulate (5) in vector form, the vector $\boldsymbol{y}$ can be expressed as

$$\boldsymbol{y} = \sqrt{\rho_{dl}} \boldsymbol{G}^\top \boldsymbol{x} + \boldsymbol{w}, \tag{6}$$

with $\boldsymbol{y} = [y_1, \ldots, y_K]^\top$ and $\boldsymbol{w} \triangleq [w_1, \ldots, w_K]^\top$. We assume i.i.d. CN(0,1) noise samples $\{w_k\}$, and a normalized $\boldsymbol{x}$ such that $\mathrm{E}\left\{\|x_k\|^2\right\} \leq 1$, corresponding to the long-term constraint on the sum of the radiated powers from the antennas. We assume availability of capacity and a reliable back-haul link between the DBSs and an existing MBS.

2.2. Unsupervised DBS trajectory selection

In practical DBS systems, the number of drones L to be deployed and their initial three-dimensional positions $T = \{z_1, \ldots, z_L\} \in \mathbb{R}^{(L\times 3)}$ are known beforehand, where z_l represents the location of the lth DBS. If we assume a minimum of $L = 3$, the DBSs can triangulate the location of the UEs based on the signal strength. The positioning matrix of the UEs obtained via the localization of the DBSs is represented as the finite three-dimensional matrix $S = \{x_1, \ldots, x_K\} \in \mathbb{R}^{(K\times 3)}$, where x_k represents the position of the kth UE. Our objective is to find the optimal matrix of DBS positions T iteratively, where $|T| = L$. The recurrent estimation of T will trace the optimal real-time trajectory of the DBS that minimizes a certain cost($\mathcal{T}$).

The first step of our algorithm assigns each kth UE to the lth DBS that presents the lowest received signal strength in the MIMO wireless network. We induce a three-dimensional *Voronoi decomposition* from the location of the DBSs into L convex cells $C_1, \ldots, C_L$ such that $C_l = \{x \in S :$ the lowest cost($\mathcal{T}$) of x_k is $z_l\}$. Rather than the conventional Euclidean cost function, $\mathrm{cost}(\mathcal{T}) = \sum_{x\in S} \min_{z\in T} \|x - z\|^2$, where z is implied in the large-scale fading estimation of the channel gain matrix $\boldsymbol{g}_k$. We minimize the received signal in (5) as follows:

$$\mathrm{cost}(\mathcal{T}) = \sum_{x \in S} \min\nolimits_{z \in T} \sqrt{\rho_{dl}}\, \boldsymbol{g}_k^{\top} \boldsymbol{x} + w_k, \tag{7}$$

Hence, each kth terminal selects the cell C_l with the lth DBS that represents the lowest $\mathrm{cost}(\mathcal{T})$ according to (7).

The second step of our algorithm updates the DBS position matrix T according to the first moment of the location of the UEs assigned to each DBS. That is, $z_l \leftarrow \mathrm{E}[C_l]$. The algorithm runs until the location of the DBSs is stabilized (i.e., until the $\mathrm{cost}(\mathcal{T})$ in (7) converges). Algorithm 1 provides a simplified pseudo-code of the process with a computational cost of $O(l|S|)$ per iteration.

Algorithm 1 Optimal trajectory search for multiple DBSs

Input: Number of DBSs L, and three-dimensional matrix of the initial positions of DBSs $T = \{z_1, \ldots, z_L\} \in \mathbb{R}^{(L \times 3)}$.
Output: Optimized DBS position matrix T, with $|T| = L$.

```
repeat (for each iteration)
  ASSIGNMENT OF UEs TO THE CORRESPONDING DBSs
    get the three-dimensional position matrix of all K active UEs.
      S = {x_1, ... x_K} ∈ R^(K×3).            ▷ By RSS triangulation
    for k = 1 : K do                            ▷ Iterate over all UEs.
      for l = 1 : L do                          ▷ Iterate over all DBSs.
        compute the k-th to l-th cost:
          cost(T) = Σ_{x_k ∈ S} min_{z_l ∈ T} sqrt(ρ_dl) g_k^T x + w_k.
        let each k-th active UE select the l-th DBS that
          represents the lowest cost(T) according to (7).
      end for
    end for
  DBS POSITIONING UPDATE
    for l = 1 : L do
      z_l ← E[C_l]
    end for
    T ← updated z_1, ..., z_L
until cost(T) converges or max. number of iterations is reached.
return T                                        ▷ Optimized DBS position matrix
```

During the run-time of Algorithm 1, the cost monotonically decreases. The algorithm will converge to a final set of DBS positions T. To prove convergence, we let $z_1^{(t)}, \ldots, z_l^{(t)}$ and $C_1^{(t)}, \ldots, C_l^{(t)}$ indicate the centers and clusters at the beginning of the tth iteration, respectively. The first step of the iteration allocates each UE to its closest DBS; therefore,

$$\mathrm{cost}\left(C_{1:l}^{(t+1)}, z_{1:l}^{(t)}\right) \leq \mathrm{cost}\left(C_{1:l}^{(t)}, z_{1:l}^{(t)}\right). \tag{8}$$

In the second step, following a generic bias–variance decomposition of random vectors

$$\mathrm{cost}(C, z) = \mathrm{cost}(C, \mathrm{mean}(C)) + |C| \cdot \|z - \mathrm{mean}(C)\|^2, \tag{9}$$

for any set $C \in \mathbb{R}^d$ and any $z \in \mathbb{R}^d$, each DBS is re-centered at its mean as

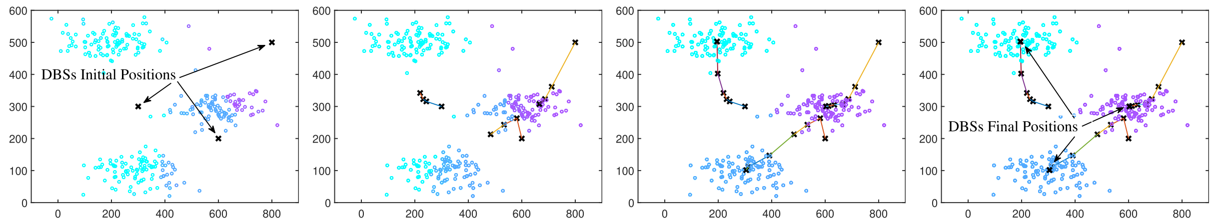
$$\mathrm{cost}\left(C_{1:k}^{(t+1)}, z_{1:k}^{(t+1)}\right) \leq \mathrm{cost}\left(C_{1:k}^{(t+1)}, z_{1:k}^{(t)}\right). \tag{10}$$

3. Simulation results and performance evaluation

To simulate the propagated signal between the DBSs and the UE, a 6 GHz MIMO channel with random scatterers is configured in MATLAB. Each DBS contains a 64-element transmitting uniform linear array (ULA). The transmitting antennas have cosine responses and the receiving antennas are isotropic. The element spacing for both arrays is less than one-half wavelength. The channel has 200 randomly generated static scatterers. The sample rate of the signal is set to 10 MHz. The altitude of the first DBS is constrained to be 50 m above the ground level, with each subsequent DBS at a separation of +1 m to avoid collision. To illustrate the simulation scenario, 300 UEs have been deployed in three highly dense clusters, with three DBSs running a trajectory selection algorithm with (1) the conventional Euclidean metric cost function, and (2) our proposed channel-dependent cost function. Fig. 1 shows the two-dimensional trajectory of the DBSs obtained with the Euclidean metric as a cost function, after 1, 4, 7, and 10 iterations. Note that the UEs are aggregated to the corresponding DBS according to the shortest distance [9–12], forming perfectly separated *Voronoi* regions. These distributions fail in considering the real characteristics of a MIMO channel; consequently, the DBSs find an expeditious path to the center of each UE distribution. Fig. 2 exemplifies the trajectory taken by the DBSs when they follow our vector quantization channel-based minimization after 1, 4, 7, and 10 iterations. Note that, starting from the first iteration (Fig. 2(a)), the simulated scatterers combined with the large-scale fading effects experienced in the MIMO channel influence the assignment of the terminals to the DBSs. In Fig. 2(b), two DBSs tend to converge, sharing the service load between the cluster of the terminals at the bottom and the one in the right. As shown in Fig. 2(c), the DBS that serves the cluster at the top still has terminals assigned at the bottom, owing to the minimization of the signal strength in the MIMO wireless network. Finally, in Fig. 2(d), the three DBSs converge to the three synthetically generated UE distributions. Fig. 3 evaluates the effect of generating the trajectory of the DBSs on the average propagation loss experienced in all the subsystems over 40 iterations. The data generated by our algorithm are compared with the data obtained from the Euclidean cost minimization. Our proposed algorithm yields a lower average propagation loss in each subsystem during the simulation. To validate our contribution further, Fig. 4 illustrates E_b/N_0 (dB) versus BER after 1, 4, 7, and 10 iterations for both cost functions under a phase shift-keying (PSK) modulation. Note that our proposed method yields a lower BER than the Euclidean minimization benchmark for all the iterations.

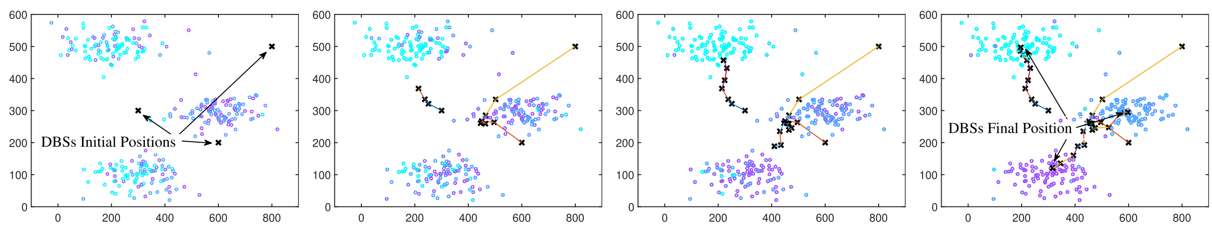
4. Conclusions and future work

Although energy-related challenges have not been comprehensively addressed yet, DBSs are highly expected to be essential to improve the QoS in 5G+ or 6G networks. We addressed the trajectory selection problem of multiple DBSs in a MIMO setting, claiming that the popular Euclidean cost function used in literature might not be ideal for a high-dynamic wireless scenario. We proposed an alternative cost function that minimizes the received signal strength instead of the conventional metric distance. Further studies can be conducted on the initialization of the location of DBSs, the impact of signal triangulation mechanisms, and inter-cell interference scenarios to achieve the maximum system performance.



(a) Iteration number 1. (b) Iteration number 4. (c) Iteration number 7. (d) Iteration number 10.

Fig. 1. Drone trajectory with the Euclidean distance as cost($\mathcal{T}$) after (a) 1, (b) 4, (c) 7, and (d) 10 iterations of the algorithm, with the horizontal and vertical axes in meters.



(a) Iteration number 1. (b) Iteration number 4. (c) Iteration number 7. (d) Iteration number 10.

Fig. 2. Drone trajectory using the proposed MIMO channel received signal strength as cost($\mathcal{T}$) after (a) 1, (b) 4, (c) 7, and (d) 10 iterations of the algorithm, with the horizontal and vertical axes in meters.

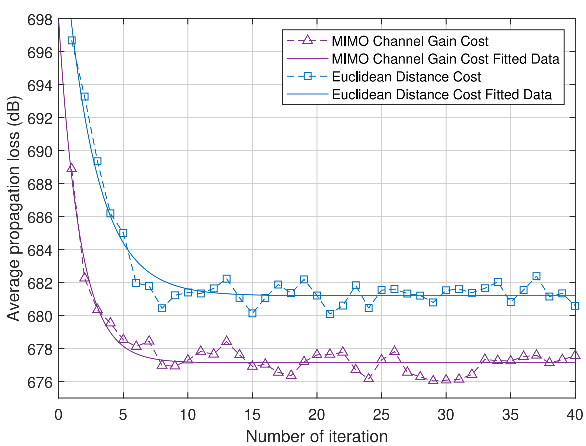


Fig. 3. Average path loss of our proposed cost function against the Euclidean metric cost used in [9–12], after 40 iterations.

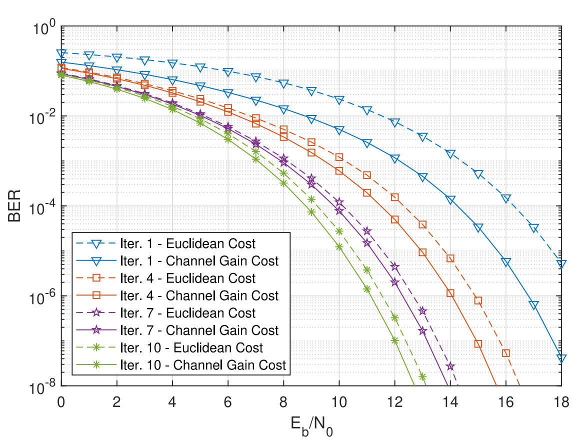


Fig. 4. E_b/N_0 (dB) vs. BER of the MIMO communication generated with our proposed cost function and the Euclidean cost function used in [9–12], after 1, 4, 7, and 10 iterations under a PSK modulation scheme.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] A. Fotouhi, H. Qiang, M. Ding, M. Hassan, L.G. Giordano, A. Garcia-Rodriguez, J. Yuan, Survey on uav cellular communications: Practical aspects, standardization advancements, regulation, and security challenges, IEEE Commun. Surv. Tutor. 21 (4) (2019) 3417–3442.

[2] S. Aggarwal, N. Kumar, Path planning techniques for unmanned aerial vehicles: A review, solutions, and challenges, 2020, pp. 270–299.

[3] S.V. Hanly, An algorithm for combined cell-site selection and power control to maximize cellular spread spectrum capacity, IEEE J. Sel. Areas Commun. 13 (7) (1995) 1332–1340.

[4] Y. Lin, W. Bao, W. Yu, B. Liang, Optimizing user association and spectrum allocation in hetnets: A utility perspective, IEEE J. Sel. Areas Commun. 33 (6) (2015) 1025–1039.

[5] J. Chen, D. Raye, W. Khawaja, P. Sinha, I. Guvenc, Impact of 3d uwb antenna radiation pattern on air-to-ground drone connectivity, in: 2018 IEEE 88th Vehicular Technology Conference, VTC-Fall, 2018, pp. 1–5.

[6] D.W. Matolak, R. Sun, Air–ground channel characterization for unmanned aircraft systems—part i: Methods, measurements, and models for over-water settings, IEEE Trans. Veh. Technol. 66 (1) (2017) 26–44.

[7] H.C. Nguyen, R. Amorim, J. Wigard, I.Z. Kovacs, P. Mogensen, Using lte networks for uav command and control link: A rural-area coverage analysis, in: 2017 IEEE 86th Vehicular Technology Conference, VTC-Fall, 2017, pp. 1–6.

[8] C.T. Cicek, H. Gultekin, B. Tavli, The location–allocation problem of drone base stations, Comput. Oper. Res. 111 (2019) 155–176.

[9] L. Liang, W. Wang, Y. Jia, S. Fu, A cluster-based energy-efficient resource management scheme for ultra-dense networks, IEEE Access 4 (2016) 6823–6832.

[10] J. Sun, C. Masouros, Drone positioning for user coverage maximization, in: 2018 IEEE 29th Annual International Symposium on Personal, Indoor and Mobile Radio Communications, PIMRC, 2018, pp. 318–322.

[11] L. Wang, Y. Chao, S. Cheng, Z. Han, An integrated affinity propagation and machine learning approach for interference management in drone base stations, IEEE Trans. Cogn. Commun. Netw. 6 (1) (2020) 83–94.

[12] H. El Hammouti, M. Benjillali, B. Shihada, M. Alouini, Learn-as-you-fly: A distributed algorithm for joint 3d placement and user association in multi-uavs networks, IEEE Trans. Wireless Commun. 18 (12) (2019) 5831–5844.

[13] L. Wang, B. Hu, S. Chen, Energy efficient placement of a drone base station for minimum required transmit power, IEEE Wirel. Commun. Lett. (2018) 1.

[14] T.L. Marzetta, E.G. Larsson, H. Yang, H.Q. Ngo, Fundamentals of Massive MIMO, first ed., Cambridge University Press, Cambridge, United Kingdom, 2016.

[15] M.E. Morocho-Cayamcela, H. Lee, W. Lim, Machine learning for 5G/B5G mobile and wireless communications: Potential, limitations, and future directions, IEEE Access 7 (2019) 137184–137206, [Online]. Available: https://ieeexplore.ieee.org/document/8844682/.

[16] E. Björnson, J. Hoydis, L. Sanguinetti, Massive MIMO Networks, first ed., now Publishers Inc., Pisa, Italy, 2019, p. 1.

[17] E. Björnson, L. Sanguinetti, H. Wymeersch, J. Hoydis, T.L. Marzetta, Massive MIMO is a reality—What is next? Digit. Signal Process. 94 (11) (2019) 3–20, [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S1051200419300776.

[18] M.E. Morocho-Cayamcela, M. Maier, W. Lim, Breaking wireless propagation environmental uncertainty with deep learning, IEEE Transactions on Wireless Communications 19 (8) (2020) 5075–5087, http://dx.doi.org/10.1109/TWC.2020.2986202.

[19] M.E. Morocho-Cayamcela, H. Lee, W. Lim, Machine learning to improve multi-hop searching and extended wireless reachability in v2x, IEEE Communications Letters 24 (7) (2020) 1477–1481, http://dx.doi.org/10.1109/LCOMM.2020.2982887.

Manuel Eugenio Morocho Cayamcela received the B.S. degree in electronic engineering from Universidad Politécnica Salesiana, Cuenca, Ecuador, in 2012, the M.Sc. degree in communications engineering and networks from The University of Birmingham, England, United Kingdom, in 2016, and the Ph.D. degree in electronic engineering at Kumoh National Institute of Technology, Gumi-si, Republic of Korea.

From 2017 to 2020 he has been a Senior Researcher with KIT Future Communications and Systems Laboratory, Gumi-si, Republic of Korea. During 2020 he worked as a Fellow Researcher with ESPOL, Guayaquil, Ecuador. Currently he is a full-time Professor at Yachay Tech University, Urcuquí, Ecuador. His research interests include communications engineering and networks, artificial intelligence, deep learning, computer vision, wireless communications, and optimization.

Mr. Morocho-Cayamcela was a recipient of the SENESCYT Fellowship from The National Secretariat for Higher Education, Science, Technology and Innovation of Ecuador in 2015, and the KIT Doctoral Grant from Kumoh National Institute of Technology in 2017.

Wansu Lim is currently an Associate Professor with the Kumoh National Institute of Technology (KIT), South Korea, leading the activities of the ICT Technologies for disabled people, Machine Learning Research and Computer Vision Processing. He was educated at the Gwangju Institute Science and Technology (GIST), South Korea, and received M.Sc. and Ph.D. degrees in 2007 and 2010, respectively. From 2010 to 2013, he was a Research Fellow at the University of Hertfordshire, U.K., and then a Postdoctoral Researcher at the Institut national de la recherche scientifique (INRS), Canada, from 2013 to 2014.

Dr. Lim is a Technical Committee member of Elsevier Computer Communications and a member of IEEE Communications Society. He has authored over 60 peer-reviewed journals and conference papers and served as reviewer for several IEEE conferences and journals.

Martin Maier is a full professor with the Institut National de la Recherche Scientifique (INRS), Montréal, Canada. He was educated at the Technical University of Berlin, Germany, and received M.Sc. and Ph.D. degrees (summa cum laude) in 1998 and 2003, respectively.

In the summer of 2003 he was a postdoc fellow at the Massachusetts Institute of Technology (MIT), Cambridge. He was a visiting professor at Stanford University, Stanford, from October 2006 through March 2007. Further, he was a co-recipient of the 2009 IEEE Communications Society Best Tutorial Paper Award. He was a Marie Curie IIF Fellow of the European Commission from March 2014 through February 2015. In March 2017, he received the Friedrich Wilhelm Bessel Research Award from the Alexander von Humboldt (AvH) Foundation in recognition of his accomplishments in research on FiWi enhanced networks. In May 2017, he was named as one of the three most promising scientists in the category "Contribution to a better society" of the Marie Sklodowska-Curie Actions (MSCA) 2017 Prize Award of the European Commission. He is the founder and creative director of the Optical Zeitgeist Laboratory (www.zeitgeistlab.ca).