Non-Asymptotic Linear Growth of Energy Efficiency in Distributed Autonomous D2D MIMO Wireless Communications

MOHAMMAD HAYAJNEH\textsuperscript{1}, (Member, IEEE), MASSA NDONG\textsuperscript{1}, NAJAH ABU ALI\textsuperscript{1}, (Member, IEEE), AND HAMIDOU TEMBINE\textsuperscript{2}, (Senior Member, IEEE)

\textsuperscript{1}Department of Computer and Network Engineering, College of Information Technology, United Arab Emirates University (UAEU), Al-Ain, UAE
\textsuperscript{2}Department of Engineering, New York University Abu Dhabi, Abu Dhabi, UAE

Corresponding author: Mohammad Hayajneh (mhayajneh@uaeu.ac.ae)

This work was supported by the ADEC Award for Research Excellence, Abu Dhabi, United Arab Emirates, under Project AARE17-019.

ABSTRACT  Device-to-device (D2D) communications is a cell-free enabler of 5G and rising wireless communications demand between low-orbit satellite constellation, self-driving vehicles and unmanned aerial systems. Distributed computation (where channel state information is not available) schemes facilitate direct exchanges between mobile user equipment (UE) and if necessary a UE can serve as a relay. Thus, it is essential to develop robust D2D communications frameworks agnostic to the channel distribution which can deliver scalable data rates to self-driving vehicles while the spectral efficiency (SE) is non-asymptotic and energy consumption is increasing to yield an energy efficiency (EE) that is a unimodal function. In this paper, we evaluate the optimal EE by using the computation of the SE in distributed multiple input-multiple output (MIMO) wireless communications. A generalized water-filling framework over arbitrary channel distribution is used to evaluate the SE and then the EE to compare with single-input single-output optimized approximate schemes based on Taylor expansion. The computation yields the optimal power allocation at the transmitters which is derived to illustrate the performance gain of the generalized water-filling distributed MIMO over the approximate scheme. Our simulations results show novel achievable EE linear growth as a function of SE and robust trade-offs in performance gains determined by the total power consumption optimal profile when switching MIMO dimensions. Our trade-off prevents power consumption while EE is decreasing. Thus by switching the number of MIMO operating antenna elements at both the receiver and transmitter sides, EE is no more a unimodal function as illustrated in the literature.

INDEX TERMS  Autonomous systems, D2D communications, energy efficiency, MIMO systems, power control, spectral efficiency.

I. INTRODUCTION

Cell free concepts have been hailed to be the future of wireless communications, and technologies such as Massive multiple-input multiple-output (MIMO) and Small cell networks are being developed to back such claim. A cell-free massive MIMO system comprised of distributed access points is proposed in [1] which shows that cell-free massive MIMO can outperform small cells in terms of per user downlink throughput (Mbits/s). Command/Control and data Communications between self-driving cars constitute an embodiment of cell free and device-to-Device (D2D) communications. D2D communications is a paradigm leading the path to cell-free wireless communications. D2D communications schemes have become ubiquitous in several areas such as intelligent transportation systems, Industry 4.0, 5G systems, etc. D2D equipment benefit from transmitting at the maximum rate possible with the least energy possible [2]–[5]. Such objective is equivalent to maximizing the energy efficiency (EE) which is measured in bit/Joule. The 3rd Generation Partnership Project (3GPP) Release 15 aims to promote D2D communications by requesting a study of power efficiency of UEs in D2D communication schemes. The review in [6] illustrates the Total Power Consumption (TPC) profiles of D2D communications schemes based on the 3GPP-LTE standardization for proximity services (3GPP...
A D2D system is primarily constituted by pairs of user equipments (UEs) able to exchange data and signaling with or without the intervention of the cellular system base station (BS). A thorough study of the potential of D2D communications requires an evaluation of the EE and its corresponding Spectrum Efficiency (SE) because of the asymptotic behavior of the SE at high Total Power Consumption (TPC) and the degradation of the EE after reaching a maximum value if TPC continues to increase. SE is defined as the number of bits that can be reliably transmitted per complex valued data symbol. Channel agnostic SE and EE are obtained by considering distributed MIMO in this paper. Joint EE-SE trade-off has been considered in the literature [8] in terms of area EE and SE. A sum of weighted area SE and area EE is optimized along fractional frequency reuse. The unimodal characteristic of the EE is not analyzed in the work. [9] presents a closed-form approximation of the trade-off between SE and EE for the uplink and downlink distributed MIMO systems. The work shows asymptotic EE behaviors similar to SE as the number of antenna elements increases and the unimodal aspect appears when EE is evaluated as a function of the distance between receiver and transmitter. The EE is asymptotic at high distances rather than being null. In [10], an EE allocation under SE constraint is proposed. The proposal optimizes the EE through joint optimal channel selection and water-filling. In this work, we avoid channel state information (CSI) estimation and EE keeps a linear increase with MIMO at optimal TPC. The trade-off between EE and SE presented in [11] is limited to showing that the EE reaches a peak value then decreases as TPC increases. Different peaks can be obtained through interference level variation. However, EE keeps decreasing after reaching a peak. As interference is a performance limiting factor in D2D communications, several mitigation schemes are reviewed in [12]. The fractional programming and sequential optimization schemes provide global optimization frameworks of the EE in [13]. A comprehensive optimization of the termed general EE and weighted EE taking into account the EE of individual transmitter-receiver links is presented. It used the link signal-to-interference-plus-noise ratio (SINR) to yield a maximum EE which is kept at such optimal constant value while TPC is increasing. In previous results, the EE degrades after reaching a maximum while TPC increases. In contrast to this work, the behavior of the corresponding SE is omitted in [13]. A study of EE and SE performance along hardware impairment is provided in [14] where Massive MIMO networks are considered. Optimal EE and SE have been considered in [15] where an approximation of the EE is proposed through Taylor series expansion in a low mean signal-to-noise ratio (SNR) regime of D2D systems considering a single antenna at both transmission and reception sides. The EE degrades after reaching a maximum. The approximate EE function is used to derive the optimal TPC transmit power where EE reaches the maximum. A theoretical approach to optimizing EE is studied in [16] under MIMO environment. Beamforming and spectrum sensing information are leveraged to optimize the EE and the SINR by transforming the non-convex EE optimization problem into a semi-definite programming problem which helps find a global maximum EE. A minimum rate of 0.1 bits/s/Hz is chosen as a constraint to derive the EE outage. The degradation of the EE after reaching a maximum and the behavior of the SE are not discussed. From the survey of the existing literature, except the work in [13], EE is a unimodal function, i.e. the 2-variable function \( EE(SE, TPC) \) is unimodal in TPC because for some given \( m > 0 \), \( EE(SE, TPC) \) is monotonically increasing for \( TPC > m \) and monotonically decreasing for \( TPC < m \). When the unimodal function \( EE(SE, TPC) \) is decreasing, SE is asymptotic and increases without providing any order of magnitude improvement. Switching the MIMO dimensions when \( EE(SE, TPC) \) starts decreasing offers large improvement on both SE and EE in our proposal.

Mobility patterns impact on D2D is a concern as highlighted in [17] because users are in and then out of range frequently. Mobility-aware D2D performance is evaluated by considering the time slots where the pair forming the D2D link are in range and a mobility parameter denoted “contact probability” is defined as the probability that both devices are in each other range. A certain list of mobility models (Random Direction Model, Brownian Motion, etc) are provided along considering the average user speed. The simulations results compare the performance of the mobility models w.r.t. downloading time (provided a suitable contact probability) and average user speed. The cellular base station assigns spectrum per user based on scheduling. There is no analysis of the coherence time impact on the mobility models or the selected time slots values in [17]. Spectral Efficiency analysis with reference to coherence time can be found in [14]. Our proposed distributed D2D MIMO scheme allows low channel state information (CSI) latencies because of the short reuse distance. It is robust to mobility induced CSI changes since the optimization is over the CSI distribution. Such method can be applied to any mobility model.

Several wireless communications scenarios occur in the context of D2D communications where distributed resource allocation algorithms are more relevant than centralized ones as illustrated in massive MIMO for communications with drones in [18]. A guide to massive MIMO with unmanned aerial vehicles (UAVs) is presented in [19] where interference management and control and command data are assigned to the UAVs quipped with the cellular base station features. D2D with UAVs is proposed in [20]. An optimal altitude is computed to cover D2D links on the ground. Resource allocation is considered in airborne communications by an optimal setting up of tethered balloons as a backhaul for UAVs traffic [21]. In Fig.1 a UAV is providing data to a self-driving car.
on the ground. Such data can be an over-the-air update of a software helping enable advance features in the vehicle navigation system. With the rise of low-orbit constellation satellite communications, vehicles and UEs can benefit from high data rate offers from line-of-sight (LOS) wireless links from satellite. The satellites and UAVs can leverage LOS and high directivity beamforming with millimeter-wave and MIMO to avoid interference and offload traffic from nearby cellular towers as illustrated in Fig.1. Such communications scenario can fit into heterogeneous networks or ad-hoc networks. The UAV and satellite may help as relays to enhance D2D communications and alleviate interference between self-driving vehicles on the ground. In [22], a joint UAV’s trajectory and power allocation optimization is proposed for the UAV to relay wireless communications. An air-to-ground 3D communication model is proposed in [23] where the UAV (acting as a relay) optimal altitude is derived and combined with opportunistic relaying where the destination receives from both source and relay. Cellular systems designs are proposed in [24] where the UAV is equipped with a base station and therefore provides an additional degree of freedom to the mobility of ground users.

In autonomous D2D communications, the UEs control the power and spectrum allocation in a distributed method. The base station provides the constraint of the maximum transmit power [12]. The work in [15] is oblivious of MIMO performance enhancement for D2D and assumes channel invariance over the two time slots dedicated to the pair of user equipment (UE) forming the D2D communications system. Furthermore, interference is not considered. In this paper, we extend the work in [15] through a distributed (where channel state information is not available) autonomous D2D communications scheme where each transceiver is equipped with more than 1 antenna element, i.e., D2D MIMO. We propose to derive the optimal EE as a function of SE in channel agnostic MIMO wireless communications. We use a generalized water-filling framework to evaluate the SE, and derive the EE by using the optimal covariance matrix from the SE and an additional circuit power consumption. Our contribution is a novel EE-SE trade-off where

- The EE values are used only when EE is increasing or reaches a peak
- The total power consumption is not increasing while EE remains constant or decreasing
- While considered in this work, the optimal TPC behavior w.r.t. EE and agnostic distribution is missing from the joint SE-EE optimization literature review.

The numerical results illustrate the performance of our approach over the scheme in [15]. Additionally, we show that the EE maxima grow linearly as the number of antenna elements at both reception and transmission sides increases. Our simulations results show novel achievable EE linear growth as a function of SE and therefore robust trade-offs in performance gains determined by the total power consumption optimal profile when switching MIMO dimensions.

The rest of the paper is structured as follows. Section II describes the system model. Section III analyses the computational scheme of the SE and EE for direct D2D communications. Section IV illustrates the numerical investigation of our approach compared to the work in [15], and further shows the behavior of the novel joint SE and EE optimization for higher MIMO dimensions. Section V concludes the paper.

II. SYSTEM MODEL

Consider a D2D MIMO system with \( J \) transmitter-receiver pairs. Each UE has \( n_t \) antenna elements and is assumed to transmit to a targeted UE with \( n_r \) antenna elements. The set of transmitter-receiver pairs is denoted by \( \mathcal{J} \). At \( t \), the transmitted signal \( s_{j,t} \) is of dimension \( n_t \) and the received signal \( y_{j,t} \) is of dimension \( n_r \). The signal model is given by

\[
y_{j,t} = H_{j,t}s_{j,t} + \sum_{j' \neq j} H_{j',t}s_{j',t} + z_{j,t},
\]

where \( t \) is the time slot index, \( H_{k,t} \) is a complex channel matrix of dimension \( n_r \times n_t \), and the vector \( z_{j,t} \) represents the noise observed at the receiver. \( z_{j,t} \) is a zero-mean circularly symmetric complex Gaussian noise vector with an arbitrary nonsingular covariance matrix. \( z_{j,t} \) can be chosen such that each of its components is of the form \( X + iY \) where \( X \) and \( Y \) are each i.i.d. following \( \mathcal{CN}(0,0.5) \). The vector of transmitted symbols \( s_{j,t}, j \in \mathcal{J} \) is characterized in terms of power by the covariance matrix \( Q_{j,t} = \mathbb{E}[s_{j,t}s_{j,t}^H] \), which is an Hermitian (self-adjoint) positive semidefinite matrix. In the low-power regime, we set small positive numbers \( p_{j,t} \), \( j \in \mathcal{J} \) such that for every transmitter-receiver pair and every time slot \( t \),

\[
\text{trace}(Q_{j,t}) \leq p_{j,t}.
\]

In the \( j \)th D2D pair communication, each component of the channel gain matrix \( H_{j,t} \) is model as Rayleigh fading gain multiplied by an average path-loss between the transmitter and receiver. The real and imaginary parts of each complex channel coefficient are Gaussian randomly distributed with zero mean and variance one half. We use matrix differential calculus [25] and the Lagrange’s multiplier method to
derive \( Q_j \). Considering the ergodic spectral efficiency \( C_j \) as the objective function, we compute \( Q_j^* \), the solution of (2). Taking the input covariance matrix \( Q_j \) as the argument to maximize \( C_j \) for each pair \( j \) enables reliable transmission at the maximum rate averaged over many coherence time periods or equivalently over many realizations of \( H_j \) where \( H_j \) is the channel matrix for the \( j \)th D2D link. Following [26], \( C_j \) is expressed as:

\[
C_j = E_m \log(\det(R_{j} + d_j^{-\alpha} H_j Q_j H_j^H)) - E_m \log(\det(R_{j})),
\]

where \( H_j^H \) is the conjugate transpose of \( H_j \), \( N_0 \sim N(0, \sigma^2 I_n) \) is the Gaussian noise, \( \alpha \) is the path loss exponent, \( d \) is the distance between the two devices of the D2D transmitter-receiver pair,

\[
R_{j} = W_j N_0 I_n + \sum_{l \neq j}^J d_l^{-\alpha} H_l Q_l H_l^H.
\]

Let us denote by \( C_{j,D2D} \) the ergodic spectral efficiency solution to (2). The instantaneous total EE and SE denoted by \( EE_j \) and \( SE_j \) respectively for the \( j \)th pair can be computed by:

\[
EE_j = \frac{W_j C_{j,D2D}}{2 \text{trace}(Q_j^*) + 2P_{\text{Circuit}}} = \frac{W_j C_{j,D2D}}{2 \text{TPC}}
\]

and

\[
SE_j = C_{j,D2D}.
\]

where \( P_{\text{Circuit}} \) is the circuit power consumption of the transmitter and TPC = trace \( Q_j^* \) + \( P_{\text{Circuit}} \). Without loss of generality, (3) and (4) assume a constant channel for each 2-time slot dedicated to the two UEs of the \( j \)th D2D pair in a one round communication.

### III. COMPUTATION OF THE OPTIMAL EE AND SE FOR DISTRIBUTED DIRECT D2D

We consider direct D2D where \( UE_1 \) transmit to \( UE_2 \) under other D2D interfering pairs. We use matrix differential calculus and the Lagrange’s multiplier method to compute \( Q_j \). The Lagrangian is given by:

\[
L(Q_j, \beta_j) = \int \log(\det(R_{j} + H_j Q_j H_j^H))m_{ij}dH_j - E_m \log(\det(R_{j})) - \beta_j(\text{trace}(Q_j) - p_{j,max}),
\]

where \( m_{ij} \) is the distribution of \( H_j \). Applying the KKT(Karush-Kuhn-Tucker) conditions for the pair \( j \) yields

\[
\begin{aligned}
\int H_j^H (R_{j} + H_j Q_j H_j^H)^{-1} H_j m_{ij} dH_j &= \beta_j m_{ij} \\
\text{trace}(Q_j) - p_{j,max} &= 0;
\end{aligned}
\]

where \( \beta_j \) is a Lagrange multiplier. We rely on computation to approximate \( Q_j^* \) because of the difficulty to derive a closed-form expression from Eq. (5). The EE is computed through the SE which is optimized using the water-filling algorithm. The water-filling algorithm stated in this paper is an optimization problem with a sum-power constraint. The number of iteration to solve the equation yielded by the KKT conditions is less than \( N_{iter} = 50 \). It depends on the initial conditions as the solution is iterative. If the initial conditions are not close to the solution, the number of iterations is very large (1000 or more). The complexity of finding the covariance matrix is \( O(2*N_{iter}) \) for each pair and thus \( O(N_{iter}*J) \) for the set of all D2D links [10]. Water-filling is a solution as shown in [25] and the problem being convex (equation yielded by the KKT conditions) ensures that the algorithm converges.

### IV. NUMERICAL INVESTIGATION

We compare the SE and EE performance of the distributed MIMO scheme to the results in [15]. The optimal \( Q_j^* \) delivers an average transmit power equal to \( p_{j,max}/n_t \). The computation of \( Q_j^* \) for \( n_r = n_t = 4 \) yields the following transmit power vectors: \( P_{t_1} = [0.244, 0.244, 0.2443, 0.246] \), \( P_{t_2} = [0.274, 0.234, 0.2343, 0.256] \), \( P_{t_3} = [0.284, 0.234, 0.2143, 0.256] \) and \( P_{t_4} = [0.194, 0.234, 0.2943, 0.256] \) where \( P_{t_i} \) is the transmit power at the \( i \)th antenna element and the \( i \)th diagonal element of \( Q_j^* \). We note that \( \text{trace}(Q_j^*) \leq p_{j,max} \) for \( p_{j,max} = 1 \). Thus, in our simulations, the transmit power for each antenna element is \( p_{j,max}/n_t \) and we chose 3 interfering UEs for the distributed MIMO scheme. Each interfering link transmits with \( p_{j,max}/(4 n_t) \) at a distance of 20 m from the desired D2D receiver link. A D2D link is comprised of 2 UEs separated by 20 m. Additional simulation parameters are presented in Table 1. The simulation results use a wideband channel bandwidth. By factoring EE with \( W_j/NB_{mw} \) where \( NB_{mw} \) is a narrow-band channel bandwidth, we can obtain narrow band results since the noise figure is randomly generated.

| TABLE 1. Simulation parameters. |
|----------------------------------|
| Parameters                     | Value         |
| Maximum BS Tx power \( P_{BS} \) | 30 W          |
| BS circuit power \( P_{C,BS} \)  | 10 W          |
| UE Tx power \( P_D \)           | 250 mW        |
| UE circuit power \( P_{C,D} \)  | 100 mW        |
| Bandwidth \( W \)              | 1 x 10^7 Hz   |
| Channel model                  | Rayleigh flat fading |
| Noise Figure                   | 7 dB          |
| Thermal Noise Density \( N_0 \) | -174 dBm/Hz   |
| Path loss for D2D link          | (148 + 40 log_{10} [d(km)]) dB |
| Path loss for cellular link     | (128.1 + 37.6 log_{10} [d(km)]) dB |

A. EE AND SE PERFORMANCE OVER THE WORK IN [15]

Fig. 2 and Fig. 3 show the performance gain in \( \text{Bits/s/Hz} \) of the SE and \( \text{Mbits/Joule} \) of the EE respectively. The curve
Direct-D2D:MIMO 2 x 2 represent our proposed distributed D2D MIMO where $n_r = n_t = 2$. This figure shows that our achieved maximum SE is more than $1.2X$ of the attained maximum SE in [15]. The attained SE in [15] is represented by the curve Direct-D2D:Simulation and the approximation is represented by the curves Direct-D2D:Analytical $N=1,3$. EE degrades after reaching a maximum while SE experiences asymptotic growth.

In applications such as massive MIMO, the high number of antenna elements increases the TPC. The TPC is a key variable affecting the EE variation of the wireless communication link. Let’s divide the TPC values into two sets $V_L$ and $V_H$ such that $x \in V_L, y \in V_H$ implies $x \leq y$. From single-input single-output to massive MIMO schemes, the EE is increasing and decreasing when the TPC value is in $V_L$ and $V_H$ respectively. The SE increases and reaches an asymptotic state as the TPC values increase. The TPC sets of values define the data rate achievable in the distributed scheme. Such asymptotic level increases widely as the number of transmit and receive antenna increases. Thus for each $x \in V_L$ (resp. $y \in V_H$), there is $x_y \in V_H$ (resp. $x_y \in V_L$) such that the EE is constant at both TCP values $x$ and $x_y$ (resp. $y$ and $y_x$). Future research can be towards finding a fast covariance matrix allocation scheme to reduce the time spent to reach the $x_y$ after leaving $x$ along the cardinality of the operating antenna elements. This is crucial to the constraints limiting the TPC maximal value because if TPC is not high enough the MIMO SE yields not the expected multi-antenna gains. TPC can is model as a sum of different power consumption components in [14] such as the CSI estimation which is performed per coherence block; Pilot decontamination is an issue considered relating to CSI.

**B. MIMO DIRECT D2D PERFORMANCE UNDER DIFFERENT VALUES OF THE TRANSMIT AND RECEIVE ANTENNAS**

After comparing our proposed EE and SE schemes to the work in [15], we illustrate the EE and SE behavior of the proposed distributed MIMO at $n_r = n_t = 2, 4, 8, 16, 32$. Fig.5 and Fig.6 show the performance gain in $\text{Bits/s/Hz}$ of the SE and $\text{Mbits/Joule}$ of the EE as $n_r$ and $n_t$ increase along with TPC. EE degrades after reaching a maximum whilst SE experiences asymptotic growth. The curve Direct − D2D : $\text{EE}(\text{TPC}^*)$ in Fig. 6 represents EE as a function of $\text{TPC}^*$ where $\text{TPC}^*$ is the TPC value where EE reaches a maximum. Finding $\text{TPC}^*$ is achieved by performing a numerical maximum search over EE values. The curve Direct − D2D : $\text{EE} vs \text{SE}(\text{TPC}^*)$ in Fig. 7 illustrates the growth and decay of EE as a function of SE at $\text{TPC}^*$ values. By switching to a higher number of antenna elements, a higher EE and SE can be obtained at a low $\text{TPC}^*$ instead of following an asymptotic SE whilst EE is decreasing. The $\text{TPC}^*$ varies slightly since Direct − D2D : $\text{EE}(\text{TPC}^*)$ is almost vertical. Direct − D2D : $\text{EE}(\text{TPC}^*)$ and Direct − D2D : $\text{EE} vs \text{SE}(\text{TPC}^*)$ illustrate the novel achievable joint SE and EE linear growth and robust trade-offs in performance gains determined by the total power consumption optimal profile when switching
the MIMO number of antenna elements at both transmit and receive sides.

In a D2D communication through a mobile-relay or a BS scenario, the considered D2D pair exchange information through a close UE denoted as $UE_R$ or a BS. Our proposal can be extended to the communications of the pairs $UE_1-UE_R$ and $UE_2-UE_R$; the case of the BS replacing the $UE_R$ can be considered as an extension which can be treated similarly. A relay scheme such as Amplify-and-Forward can be considered to evaluate the performance of the relay D2D communication type. Regarding the computation of $SE$ and $EE$ of the relay scheme, since each $UE_k, k = 1, 2$ is transmitting to the relay, each $Q_k, k = 1, 2$ can be computed using the derivation in SectionIII while considering the channel between each $UE_k, k = 1, 2$ and the relay which is analogous to the direct D2D case without relay terminal. In vehicular technology, platooning requires high rate and reliable exchange of information exchange to keep the stability of the vehicle set. Such requirement could be met by using the above presented distributed MIMO scheme. In an adaptive control of a fast power allocation. Thus, a fast adaptive power control which switches between the SE and the EE performance can be devised to find a trade-off satisfying an EE threshold while gaining on SE.

The switching of the number of antennas at both receiver and transmitter sides offers the opportunity to gain in EE and SE, thus presents a better trade-off. If a user state is in the decreasing EE, a bimodal EE function can be obtain by the switching where a new maximum of EE and SE can be reached before reaching the asymptotic level of SE.

V. CONCLUSION

In this paper we have analysed and provided some insights into the design of MIMO D2D communications in terms of EE and SE. The EE is derived from the optimal covariance matrix of the MIMO SE without consideration of channel estimation. The joint optimization of the EE and SE depends fundamentally on the total power consumption (TPC). We have shown that by using the TPC*, we can achieve novel joint SE and EE linear growth and robust trade-offs in performance gains determined when switching MIMO dimensions. Additionally, our results have shown that EE is a linear function of SE at TPC* when the number of antenna elements at both sides varies.

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HAMIDOU TEMBINE (Senior Member, IEEE) received the degree in applied mathematics from École Polytechnique, Palaiseau, France, in 2006, and the Ph.D. degree in computer science from INRIA and the University of Avignon, in 2009. He was previously a Faculty Member of École Superieure d’Electricite, France. He has been an Assistant Professor of electrical and computer engineering with New York University Abu Dhabi, since 2014. He is a prolific researcher and holds several scientific publications in magazines, letters, journals, and conferences. He has authored the book Distributed Strategic Learning for Wireless Engineers (CRC Press and Taylor & Francis, 2012), which received the book award in the category of science and engineering, in 2014, and coauthored the book Game Theory and Learning for Wireless Networks: Fundamentals and Applications (Elsevier and Academic Press). His main research interests are in game theory and learning. He has been the co-organizer of several scientific meetings on game theory in networking, wireless communications, and smart energy systems. His research interests include evolutionary games, mean-field stochastic games, distributed strategic learning, and applications in engineering, biology, and economics. In 2014, he received the IEEE ComSoc Outstanding Young Researcher Award for his promising research activities for the benefit of the society. He was a recipient of five best paper awards in the applications of game theory.

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VOLUME 8, 2020