ACQUISITION OF CHANNEL STATE INFORMATION IN HETEROGENEOUS CLOUD RADIO ACCESS NETWORKS: CHALLENGES AND RESEARCH DIRECTIONS

GONGPU WANG, QIANG LIU, RUISI HE, FEIFEI GAO, AND CHINTHA TELLAMBURA

ABSTRACT

As an emerging system architecture, heterogeneous cloud radio access networks (H-CRANs) can improve system capacity, enlarge coverage, and enhance energy/spectral efficiency. Meanwhile, this newborn architecture also brings many open problems for traditional topics, including synchronization, channel estimation, and data detection. In this article, we present a comprehensive analysis on obtaining CSI in H-CRANs. Specifically, we recognize seven challenges in channel estimation that are caused by a large number of channel parameters, heterogeneity of access nodes in H-CRANs, and the time delays among different nodes. Several research directions for handling these challenges are also proposed, for example, array signal processing and channel compression can eliminate the number of channel estimates, while channel prediction and modification for high-speed railway communications and adaptive downlink array from uplink measurements excel in overcoming the non-reciprocity in channel parameters.

Gongpu Wang and Qiang Liu are with Beijing Jiaotong University.

Ruisi He is with Beijing Jiaotong University.

Feifei Gao is with Tsinghua University.

Chintha Tellambura is with University of Alberta.

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INTRODUCTION

The past four decades have witnessed a rapid proliferation of wireless networks and transmission technologies. Cellular networks have evolved from the first generation (1G) analog system in the 1980s to the second generation (2G) digital system in the 1990s to the third generation (3G) code-division multiple access (CDMA) system in the 2000s, and then to the fourth generation (4G) orthogonal frequency-division multiplexing (OFDM) plus multiple-input multiple-output (MIMO) system in the current decade.

The popularity of smart mobile phones and the appearance of high-definition applications such as high-quality video streaming continue to impose an increasing demand for high data rate wireless access and services on the existing cellular networks. It is estimated that mobile data traffic will grow 24 times between 2010 and 2015, and more than 200 times between 2010 and 2020 [1].

Heterogeneous networks (HetNets) have been proposed and are recognized as an effective architecture to meet the explosive growth of mobile data traffic [2]. A HetNet mainly consists of two types of nodes: low-power nodes (LPNs) and high-power nodes (HPNs). The LPN includes small cell base stations (BSs), femto BSs, and pico BSs, while the HPN contains macro and micro BSs. In a HetNet, LPNs and HPNs cooperate to provide high data services and ubiquitous coverage for user terminals (UTs), which is often referred to as coordinated multipoint (CoMP) transmission. Although CoMP can provide large cooperative gains and improve data rates of cell edge users, it still has some disadvantages in terms of spectral efficiency (SE) and energy efficiency (EE) due to the backhaul constraints, overhead channel delay, channel estimation accuracy, and high requirements on synchronization.

To further improve SE and EE of CoMP, a new system architecture named the heterogeneous cloud radio access network (H-CRAN) was proposed in [3] that benefits from cloud computing and converging network units. In an H-CRAN, the HPNs are installed with massive antennas, and the LPNs are connected via high-speed optical fibers to a cloud often referred to as a baseband unit (BBU) pool. In addition, the LPNs only deal with RF band signal processing, while the cloud covers baseband signal processing for all LPNs. This centralized or autocracy-like position of the cloud can provide better cooperation between BSs and lower the total energy consumption.

It is worth noting that the architecture of the H-CRAN is similar to that of cloud radio access networks (C-RANs) [4]. The main differences between H-CRANs and C-RANs are the incorporation of HPNs in the H-CRAN and an evolu-

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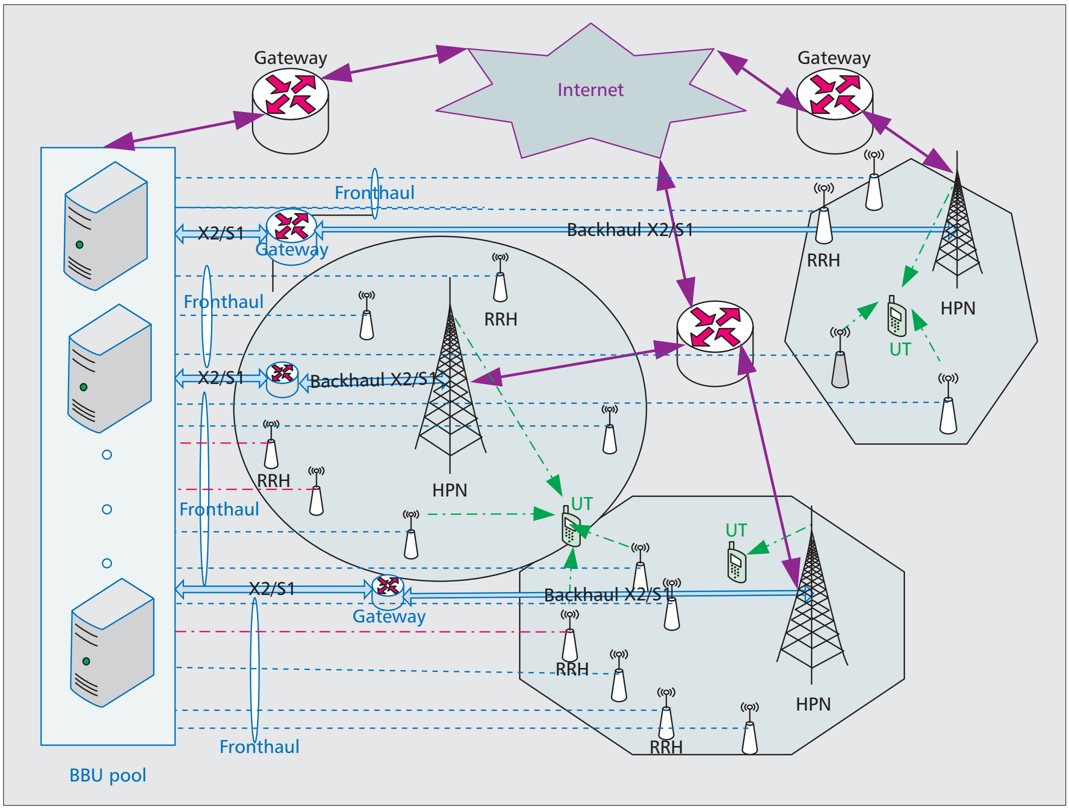

Figure 1. System architecture of H-CRANs.

Depending on carrier frequency, transmitted symbol rates, velocities of mobile users, system bandwidth, and surrounding environments, wireless channels can be classified into four kinds: flat-fading time-invariant, frequency-selective time-invariant, flat-fading time-varying, and doubly selective channels.

tion from C-RAN to H-CRAN. On one hand, HPNs in an H-CRAN connect to the cloud via the new data interface S1 and the control interface X2 that a C-RAN does not have. On the other hand, HPNs transmit all control signaling and system broadcasting messages to UTs, which can reduce the time delay constraints between the cloud and UTs.

Generally speaking, the H-CRAN, as a fresh thing, can bring better system performance such as enlarged capacity, enhanced coverage, and improved SE and EE, and at the same time introduce many challenges and open problems. For example, channel modeling and capacity analysis for H-CRANs remain unknown, and interference analysis in H-CRANs is a recognized challenge [3].

To the best of our knowledge, most existing works about HetNets, C-RANs, and H-CRANs assume perfect channel state information (CSI), and only a few works address the challenges in channel estimation, which motivate our current work. In this article, we present a comprehensive survey on technological problems in obtaining CSI in H-CRANs and also provide possible research directions. It is shown that the numerous channels, heterogeneity, and transmission delays are the three main factors that lead to difficulty in obtaining CSI.

The remainder of this article is organized as follows. We present the architecture of H-CRANs and describe the charateristics of channel parameters in H-CRANs. A brief summary of current channel estimators and their applications in H-CRANs is introduced. The challenges in channel estimation are analyzed, and corresponding research directions are also suggested before drawing the conclusion.

H-CRAN and Its Channel Parameters

H-CRAN Architecture

Figure 1 illustrates the system structure of a typical H-CRAN where UTs can access the H-CRAN and Internet via remote radio heads (RRHs) or HPNs; HPNs are cellular BSs with massive linear, rectangular, cylindrical, or spherical antennas; RRHs can be simplified 3G or 4G BSs, or access points for wireless local area networks (WLANs) with IEEE 802.11 protocols, or BSs operating at millimeter-wave such as IEEE 802.16. Note that RRHs only deal with the RF band signal processing in the physical layer, and leave all other jobs to the cloud (BBU pool), including baseband estimation and detection in the physical layer, functionalities of the medium access control (MAC) layer, and procedures in the network layer.

The signals between UTs and nodes (LPNs or HPNs) in an H-CRAN can be categorized into three types: control signaling, voice messages, and data packages. All control signaling and system broadcasting messages will be transmitted by HPNs to UTs. The voice messages and low-rate data messages will also be administrated by HPNs. High data rate packages will be mainly served by RRHs. When some UTs require very high data rate service at the edge of a cell, it is possible that both HPNs and LPNs in the cell, together with LPNs in the neighbor cell, will cooperate to meet the large traffic demand of UTs.

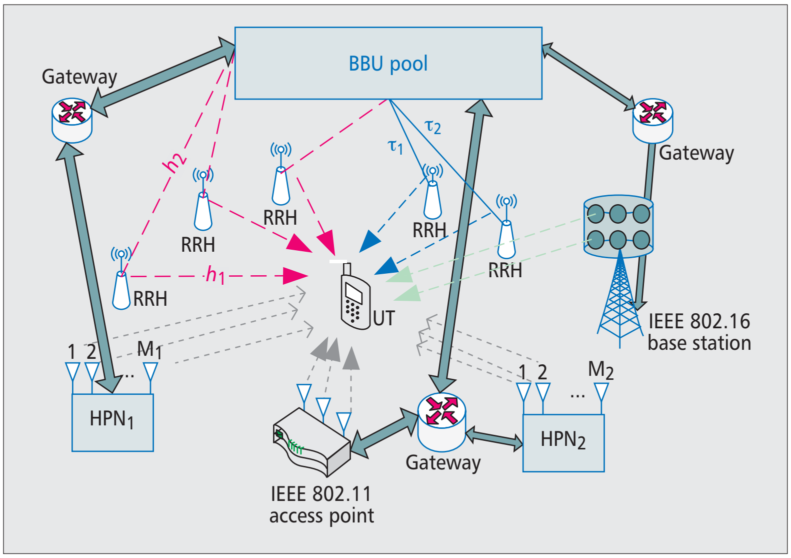

Figure 2. Channels in an H-CRAN.

Channel Parameters in H-CRANs

Figure 2 depicts one typical scenario in which a UT communicates with potential access nodes in an H-CRAN. The wired and wireless channels between the UT and the nodes are shown as solid and dashed lines, respectively. The links between a BBU pool and RRHs can be wireless or wired, so RRHs can play the role of relays or remote RF transceivers. When an RRH acts as a relay node, the concatenated channel includes two parts: wireless channel h_1 between the UT and the RRH, and wireless channel h_2 between the RRH and the BBU pool. In this case, estimators for cooperative networks can be applied to obtain convoluted CSI [7]. When the RRH connects the BBU pool with a wired link such as optical fiber or twist pairs, the time delays τ_1 and τ_2 between the RRH and the BBU pool are important channel parameters that do not exist in traditional point-to-point or cooperative communication systems. Besides, one UT can also access the network through not only HPNs, but also IEEE 802.11 access points and IEEE 802.16 BSs. Clearly, these available wireless channels for the UT are plentiful and heterogeneous.

Therefore, due to the increasing number of antennas, the heterogeneity of access nodes [3], as well as the time delays of transmitting packages between BBU pool and RRHs, channel estimation is a more challenging issue for H-CRANs.

Existing Channel Estimators and Their Applications in H-CRANs

Depending on carrier frequency, transmitted symbol rates, velocities of mobile users, system bandwidth, and surrounding environments, wireless channels can be classified into four kinds: flat-fading time-invariant, frequency-selective time-invariant, flat-fading time-varying, and doubly selective channels. For most wireless communication systems, channel estimates are required by wireless nodes to perform essential tasks such as precoding, beamforming, and data detection. To obtain the estimates of the channel parameters, different training sequences are transmitted in various communication systems.

For traditional point-to-point wireless systems with time-invariant channels, the most popular estimators are the maximum likelihood (ML) method and minimum mean square error (MMSE) approach. Assuming that the noise is Gaussian-distributed, the ML method can be simplified to a least squares (LS) estimator, while with a Gaussian assumption for both noise and channels, the MMSE estimator will find its close-form solution, often called linear MMSE (LMMSE) estimates.

For traditional point-to-point wireless systems with time-varying channels, only CSI at a limited set of time instances can be estimated because the data symbols are transmitted at other time instances. To solve this problem, time-varying channels are represented by the Gauss-Markov model (GMM) [6], which tracks channel variation through symbol-by-symbol updating, and by the basis expansion model (BEM) [5], which decomposes the channel into the superposition of the time-varying basis functions weighted by time-invariant coefficients.

For cooperative networks with amplify-and-forward (AF) mode, the channel estimators are different from those in traditional point-to-point systems [7] due to channel concatenation. Furthermore, it has been pointed out in [9] that channel estimators for one-way relay networks (OWRNs) and two-way relay networks (TWRNs) vary considerably due to self-cancellation at both source terminals in TWRNs.

The existing typical channel estimation approaches for traditional point-to-point networks and cooperative networks, as well as their possible applications in H-CRANs, are briefly summarized in Table 1, which indicates that there are many open problems about channel estimation in H-CRANs.

Challenges on Channel Estimation in H-CRANs

In this section, we analyze the challenges on obtaining the channel parameters in H-CRANs.

What and How Many Channel Parameters Are to Be Estimated

The first step in obtaining CSI in H-CRANs is to decide which and how many parameters are to be estimated. Channel parameters include channel statistics such as means and variances, and instantaneous CSI. The time delays of package transmissions between RRHs and the BBU pool can also be key channel parameters that influence bit error rate (BER) performance and system capacity.

For one UT with a single antenna, there may be many wireless channels between the UT antenna and RRHs' antennas around the UT. HPNs are often equipped with massive antennas; hence, there are also abundant channels between the UT and nearby HPNs. Acquisition of all these instantaneous channel parameters is

Channel types and expressions	Point-to-point networks	Cooperative networks	Applicable in H-CRANs
Flat-fading time-invariant channel $y(n) = hx(n) + w(n)$	ML MMSE	OWRN [7], TWRN [9], multihop [10]	Applicable in a few cases [8]
Frequency-selective time-invariant channel $y(n) = \sum_{l=0}^{L-1} h_l s(n-l) + w(n)$	LS LMMSE	OFDM	Adaptable in some cases
Flat-fading time-varying channel $y(n) = h(n)x(n) + w(n)$	BEM [5] GMM [6]	TWRN [11]	To be exploited
Doubly selective channel $y(n, l) = \sum_{l=0}^{L-1} h_l(n)s(n-l) + w(n)$	BEM + LMMSE BEM + GMM + Kalman filter	EM + zero padding	Not studied yet

Table 1. List of channel types and corresponding estimators.

resource-consuming and complexity-increasing for the BBU pool, and is almost impossible in a practical situation, especially when the channel coherence time is short. Clearly, selecting some channel parameters for estimation is necessary for H-CRANs; thus, problems arise:

- How is the channel subset chosen from many existing channels with instantaneous values unknown to the BBU pool?
- How large should the subset be to satisfy the data rate requirements and transmit power limits as well as the minimal interference constraints?

To our best knowledge, only a few studies have investigated the above two problems in C-RANs [14], and the exact solutions for H-CRANs have yet to be developed.

Massive MIMO and Pilot Contamination

HPNs are often equipped with massive receiving antennas, which can enable high-throughput delivery between HPNs and UTs [12]. The large number of antennas in HPNs can construct ample wireless channels for one UT; this also brings about the well-known problems of channel estimation and pilot contamination. As shown in Fig. 3, HPN_0 in the central cell receives both pilots indicated by the blue line from UT_0, and pilots depicted in red dashed lines from UT_i $(1 \le i \le K)$ in the K neighbor cells. The latter K pilots "contaminate" the first pilot sequence during the channel estimation process and reduce the estimation accuracy achieved by HPN_0.

Frequency-Division Duplexing

Existing studies assume that H-CRANs operate in a time-division duplexing (TDD) mode. This assumption will result in the same CSI for both forward and reverse channels. Thus, the training sequence transmitted by one UT and received at HPNs and RRHs can be utilized to estimate uplink CSI due to reciprocity. However, for H-CRANs with frequency-division duplexing (FDD) mode, this method does not work because the uplink and downlink channels have different wavelengths and thus various responses. Moreover, the common method of acquiring CSI — transmitting downlink pilots over different time slots by HPNs or RRHs in a predefined order so that UTs can receive and estimate the channel parameters — is not practical in H-CRANs due to the large number of wireless channels and limited channel coherence time. Therefore, how to obtain downlink CSI is an interesting and difficult task for FDD H-CRANs.

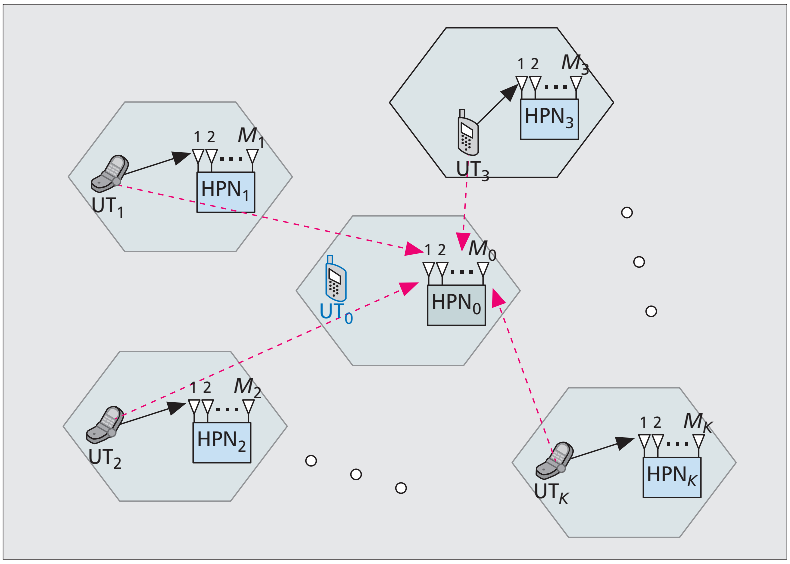

Figure 3. Pilot contamination for HPN_0 in an H-CRAN.

Time-Varying Channels

The UTs may be mobile smartphones (MSPs), and the mobility of MSPs can introduce Doppler shift in frequency, which can result in time-varying wireless channels between the MSP and RRHs/HPNs. The higher velocities of MSPs can produce variances in the these channel parameters, thus introducing difficulty in obtaining accurate CSI. Such cases often take place for UTs on highways or high-speed railways (HSRs).

Time Delays and Outdated CSI

Due to the transmission delay of pilot and data transmission from RRHs to a BBU pool (e. g., τ_1 and τ_2 in Fig. 2), the CSI obtained at the BBU pool is outdated at the moment of deciding which UT should be chosen for transmission and also at the following moment of UT data transmission. Currently, few studies provide modeling of time delays in mathematical expressions. How to evaluate and overcome the influ-

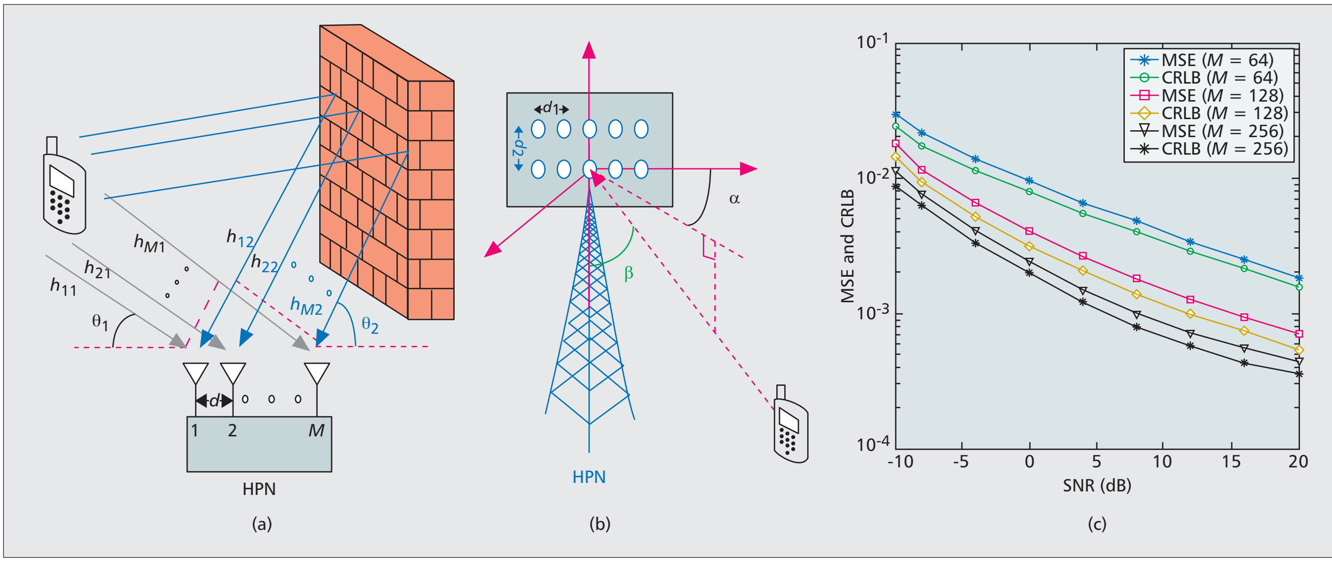

Figure 4. Wireless channels between one UT and one HPN: a) HPN with linear antennas; b) HPN with planar antennas; c) estimation MSE and CRLB vs. SNR, where M denotes the number of pilots.

ence of outdated CSI in H-CRANs remains unknown and deserves further investigation.

Channel Estimation Errors and Training Sequence Design

Due to the existence of noise and interference, channel estimation errors are inevitable in the estimates of channel parameters. Since the channel matrices between UTs and HPNs/RRHs are large, the influence of the channel estimation error is non-negligible, and the corresponding robust beamforming schemes are nontrivial problems.

One choice to reduce channel estimation errors is transmitting more pilot symbols. Although transmitting more training sequences can increase accuracy in channel estimation, it introduces more pilot contamination in H-CRANs. Therefore, how many trainings are needed for RRHs and HPNs is another interesting problem. In addition, the training sequence design for H-CRANs, such as power allocation, pilot position, and transmission intervals, differs from that in point-to-point or cooperative networks and contains a series of optimization problems. The objective functions for the training sequence design in traditional cellular networks are often assumed as minimizing the estimation mean square error (MSE) or maximizing the capacity/throughput or the lower bounds. However, for H-CRANs, maximizing the area spectral efficiency (bits per second per Hertz per square meter) may be a good choice for the objective function in the training sequence design [2].

Different Requirements on Estimation Accuracy

Another feature for channel estimation in H-CRANs is that different links have various channel parameters and thus impose diverse requirements on estimation accuracy. For example, in Fig. 2 the wireless link h_1 between the BBU pool and the RRH is almost static while the wireless channel h_2 between the RRH and the MSP can be both time-varying and frequency-selective due to the mobility of the MSP. Therefore, to obtain estimates for channel h_1 requires far fewer training symbols than for channel h_2. In such a case, joint training sequence design for both fronthaul and access links can be a good choice.

Research Directions

It is shown above that the challenges in the acquisition of CSI in H-CRANs come from the large number of channel parameters, the heterogeneity of system components, and the time delays of package transmission. In this section, five research directions are proposed for channel estimation in H-CRANs.

Array Signal Processing

Since the massive antennas in HPNs are often aligned regularly, the wireless signal transmitted from one UT will arrive at the receiving antennas in an ordered form. For one channel tap, the difference in the channel gains between neighbor receiving antennas can be simplified as only phase change. More importantly, the phase difference can be mathematically described in most cases when the antennas are located regularly. This can be visualized through Fig. 4a, where channels between one UT with a single antenna and one HPN with M linear antennas are plotted in the case of two channel taps. For the ith (i = 1, 2) tap, the M channels $[h_{1i}, h_{2i}, \cdots, h_{Mi}]$ from the UT antenna to the HPN antennas can be expressed as $h_{1i}\,[1, e^{j2\pi d\cos\theta_i/\lambda}, \cdots, e^{j2\pi(M-1)d\cos\theta_i/\lambda}]$, where λ denotes the wavelength, d is the distance length between two antennas of the HPN, and θ_i represents the angle of arrival (AoA) for the ith channel tap shown in Fig. 4a. Therefore, utilizing techniques of array signal processing, we can first obtain estimates of the angle parameters θ_1 and θ_2 and reference fading

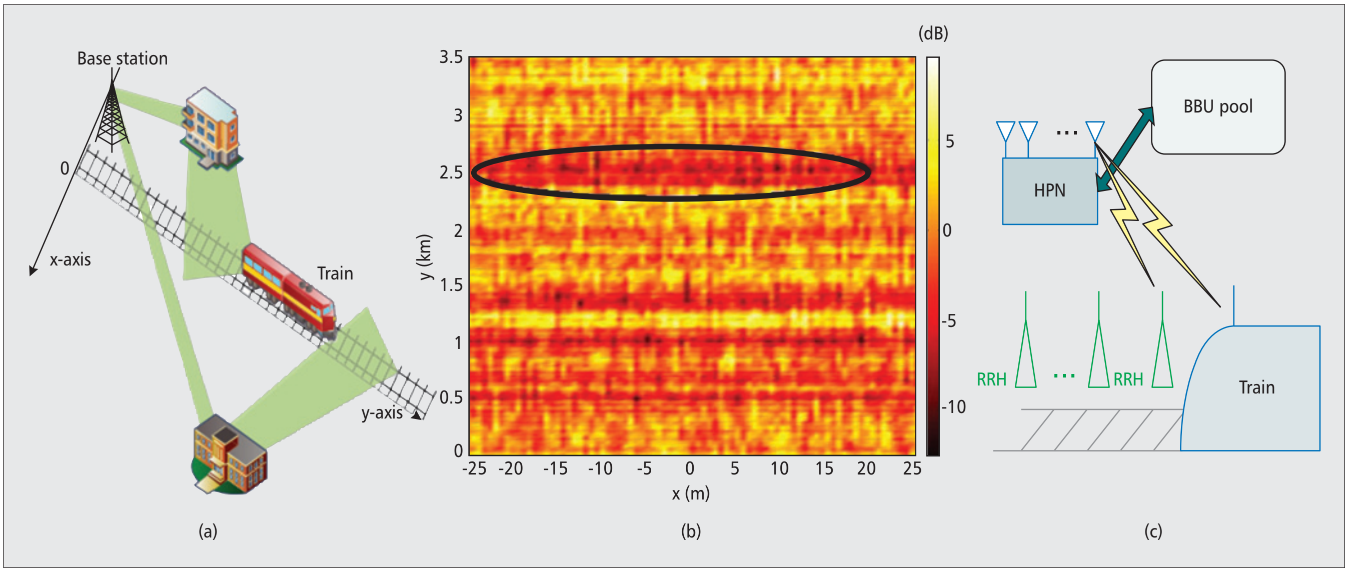

Figure 5. a) Illustration of a typical HSR propagation environment, where green tracks represent the propagation of MPCs; b) simulated shadow fading components along an HSR track, where the small-scale fading and distance-dependent path loss are removed for clarity; c) an H-CRAN on HSR, where some RRHs are along the railway, and the channel parameters between HPNs and train antennas are correlated with those between HPNs and RRHs close to the train.

coefficient h_{11} and h_{M2}, and then recover all channel parameters.

Similarly, as shown in Fig. 4b, for HPNs with rectangular antenna array, the parameters to be estimated in each tap are simplified to the reference fading coefficient, azimuth angle α, and elevation angle β, which are much fewer than the large number of channel parameters of this tap between the UT and the HPN.

Figure 4c illustrates the MSE of the channel estimates vs. signal-to-noise ratio (SNR) when utilizing array signal processing to obtain CSI for one HPN with linear antenna array. It can be seen that the estimation MSEs approach the corresponding Cramer Rao lower bounds (CRLBs), and the gap between MSEs and CRLBs is due to pilot contamination. Moreover, such gap can be further reduced through robust transceiver design [13]. Clearly, array signal processing is an effective method to reduce the number of channel estimates with acceptable estimation performance.

Selection and Compression

When both RRHs and HPNs, or many RRHs cooperate to provide high data rate service for one UT, the wireless channels are heterogeneous (i.e., different channels have different propagation losses). In such a situation, one interesting question arises: can we directly choose some channels for estimation before transmitting pilots? Reference [14] provided the answer with an innovative CSI acquisition scheme called *compressive CSI acquisition*. It assumes that statistical CSI on all channels is available at the BBU pool, sets a SNR threshold to choose channels, and aims at minimizing total transmission power. The channels can be chosen through semi-definite programming (SDP) and Gaussian randomization after certainty-equivalent formulation. Next, the parameters of the chosen channels will be estimated, based on which the beamforming matrix can be designed.

Prediction and Modification for HSR Communication

Different from personal UTs roaming around the H-CRAN, the antennas on the train and UTs in the train follow fixed tracks of the railways, and their arrival time at each place comply with a strict preplanned schedule.

A typical HSR propagation environment is illustrated in Fig. 5a, where we can see that for a certain BS-train separation distance, the received multi-path components (MPCs) by UTs in the train are mostly affected by the same obstacles and suffer from similar attenuations. This leads to cross-correlation between BS-train links on both large- and small-scale fading domains.

In Fig. 5b, shadow fading components within a narrow-strip-shaped region along an HSR track are simulated based on the reported measurements. It can be found that within the narrow-strip-shaped region along the HSR track, the signals with different x indices usually attenuate at the same distance (e.g., y = 1, 1.5, and 2.5 km in Fig. 5b). This means that for the typical HSR environment, the radio channels of different links are correlated.

Therefore, the channel parameters for the UTs on HSRs in an H-CRAN can be forecast and modified, instead of estimated. Figure 5c depicts a scenario where channel prediction and modification can be utilized in an H-CRAN on HSR. Since some RRHs are distributed along the railways, the channels between the HPN and the train antennas are correlated with those between the HPN and the RRHs. The HPNs and the BBU pool can thus obtain channel estimates from the communication process of last trains or nearby RRHs, predict the current channel parameters, and modify these predictions according to the received symbols. In addition, combining with technologies of big data or data mining, channel prediction and modification can

GMM can also be a good choice to model the channels in consecutive symbol durations and thus can be utilized to evaluate the effects of the time delays described earlier. Besides, superimposed pilots can be transmitted together with data symbols, which requires no extra bandwidth.

obtain good performance in both estimation MSE and throughput due to avoiding the high cost of estimating the abundant time-varying parameters.

Another way to reduce the number of channel estimates is to express the channel parameters on an orthogonal basis with limited coefficiencies. The number of coefficiencies should be much less than that of channel parameters. The basic idea is the same with BEM suggested in [5]. Apart from BEM, GMM can be an alternative to approximate the numerous channels. In addition, GMM can also be a good choice to model the channels in consecutive symbol durations, and hence can be utilized to evaluate the effects of the time delays described earlier. Besides, superimposed pilots can be transmitted together with data symbols, which requires no extra bandwidth. Therefore, superimposed pilots can be utilized to track the time-varying channel at the cost of reduced data power.

Adapting Downlink Array from Uplink Measurements

For H-CRAN with FDD mode, it is not practical to estimate downlink channel parameters based on uplink estimates due to non-reciprocity of the unlink and downlink. On the other hand, sending training sequences from HPNs and RRUs to UTs can be one way to estimate downlink parameters. However, a large number of training sequences are required.

The novel idea suggesed in [15] may be a good solution to this dilemma in an FDD H-CRAN: obtaining a downlink beamforming matrix directly from uplink measurements, instead of estimating downlink channel parameters. Aimed at maximizing the SNR of the desired UT, the beamforming vector can be obtained by solving an eigenvector and eigenvalue problem with no requirement on information about downlink channel parameters. It is shown in [15] that this method can provide improvements in downlink SNR even when only one snapshot of uplink array response is available.

Conclusions

In this article, we have summarized the characteristics of H-CRAN channels, surveyed the existing estimators as well as their applications in H-CRANs, and investigated the current challenges to obtaining CSI in H-CRANs. It is shown that these challenges result from different factors such as a large number of channel parameters to be estimated, heterogeneity of access nodes in H-CRANs, and packet transmission delays. Accordingly, five possible research directions have also been suggested to overcome these three difficulties.

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Biographies

Gongpu Wang (gpwang@bjtu.edu.cn) received his B.Eng. degree in communication engineering from Anhui University, Hefei, China, in 2001 and his M.Sc. degree from Beijing University of Posts and Telecommunications (BUPT), China, in 2004. From 2004 to 2007, he was an assistant professor in the School of Network Education, BUPT. He received his Ph.D. degree from the University of Alberta, Edmonton, Canada, in 2011. After graduation, he joined the School of Computer and Information Technology, Beijing Jiaotong University (BJTU), China, where he is currently an associate professor. His research interests include wireless communication theory and signal processing technologies.

Qiang Liu (liuq@bjtu.edu.cn) received his M.S. and Ph.D. degrees in communication and information systems from the Beijing Institute of Technology (BIT) in 2004 and 2007, respectively. After graduation, he joined the School of Computer and Information Technology, BJTU, China, where he is currently an assistant professor. His research interests include wireless communication networks and network simulation technologies.

Ruisi He [S'11, M'13] (ruisi.he@ieee.org) received his B.E. and Ph.D. degrees from BJTU in 2009 and 2015, respectively. He is currently an asociate professor with the State Key Laboratory of Rail Traffic Control and Safety, BJTU. From 2010 to 2014, he was a visiting scholar at Universidad Politécnica de Madrid, Spain, the University of Southern California, and Université Catholique de Louvain, Belgium. His current research interests are in the field of measurement and modeling of wireless propagation channels, antennas, and signal processing. He received the URSI Young Scientist Award in 2015.

Feifei Gao [S'05, M'09] (feifeigao@ieee.org) received his B.Eng. degree from Xian Jiaotong University, China, in 2002, his M.Sc. degree from McMaster University, Hamilton, Ontario, Canada, in 2004, and his Ph.D. degree from National University of Singapore in 2007. He was a research

fellow with the Institute for Infocomm Research, A*STAR, Singapore, in 2008 and an assistant professor with the School of Engineering and Science, Jacobs University, Bremen, Germany, from 2009 to 2010. In 2011, he joined the Department of Automation, Tsinghua University, Beijing, China, where he is currently an associate professor. He also serves as an adjunct professor with the School of Engineering and Science, Jacobs University. He has coauthored more than 80 refereed IEEE journal and conference proceeding papers. His research interests are communication theory, broadband wireless communications, signal processing, multiple-input-multiple-output systems, and array signal processing.

CHINTHA TELLAMBURA [F'11] (chintha@ece.ualberta.ca) received his B.Sc. degree (with first-class honors) from the University of Moratuwa, Sri Lanka, in 1986, his M.Sc. degree in electronics from the University of London, United Kingdom, in 1988, and his Ph.D. degree in electrical engineering from the University of Victoria, British Columbia, Canada, in 1993. He was a postdoctoral research fellow with the University of Victoria (1993–1994) and the University of Bradford (1995–1996). He was with Monash University, Melbourne, Australia, from 1997 to 2002. Presently, he is a professor with the Department of Electrical and Computer Engineering, University of Alberta. His current research interests include multiple antenna and multicarrier communication systems, cognitive radio, and relay networks.