Dynamic Base Station Formation for Solving NLOS Problem in 5G Millimeter-Wave Communication

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***Abstract*—Millimeter-wave communication is one of the enabling technologies to meet high data-rate requirements of 5G wireless systems. Millimeter-wave systems due large available bandwidth enable gigabit-per-second data rates for line-of-sight (LOS) transmissions in short distances. However, for non-line-of-sight (NLOS) transmissions, millimeter-wave systems suffers performance degradation because the received signal strengths at user equipments (UEs) are not satisfactory. In this paper, the NLOS problem in millimeter-wave systems is treated from SoftAir (a wireless software-defined networking architecture) perspective. In particular, a so-called dynamic base station (BS) formation is introduced, which adaptively coordinates BSs and their multiple antennas to always satisfy UEs' quality-of-service (QoS) requirements in NLOS cases. First, the architecture for software-defined millimeter-wave system is introduced, where remote radio heads (RRHs) coordination is explained and millimeter-wave channel model between RRHs and UEs is analyzed. A ubiquitous millimeter-wave coverage problem is formulated, which jointly optimizes RRH-UE associations and beamforming weights of RRHs to maximize the UE sum-rate while guaranteeing QoS and system-level constraints. After proving the np-hardness of the coverage optimization problem with non-convex constraints, an iterative algorithm is developed for dynamic BS formation that achieves ubiquitous coverage with high data rates in LOS and NLOS cases. Through successive convex approximations, the proposed dynamic BS formation algorithm transforms the original mixed-integer nonlinear programming into a mixed-integer second-order cone programming, which is efficiently solved by convex tools. Simulations validate the efficacy of our solution that completely solves NLOS problem by facilitating ubiquitous coverage in 5G millimeter-wave systems.**

I. Introduction

Millimeter-wave communication at 30-300 [GHz] is one of the enabling technologies to meet high data-rate requirements (10 [Gbps] peak rate and 100 [Mbps] cell-edge rate) of 5G wireless systems [1], [2]. This new-type communication brings much wider transmission bandwidths (500 [MHz] or more per channel as compared with 5-20 [MHz] in current microwave communication), and the small wavelength facilitates large antenna array and antenna technology at base stations (BSs). However, experiments [3] show that millimeter-wave communication suffers from several limitations (e.g., short-range distances, inevitable blockage effects, and sparse-scattering radio patterns). At this high band [4], energy consumption dramatically increases due to air absorption and shortens communication distances even for line-of-sight (LOS) transmissions. Moreover, obstacles (like buildings, vehicles, tree branches, foliage) may block signals and cause non-line-of-sight (NLOS) transmission problems. Also the sparse scattering induces increased channel correlation and narrow beams with less side lobes. These problems jointly impede millimeter-wave transmissions with obstacles and directional beams, causing the NLOS problem.

To overcome the NLOS challenge in millimeter-wave communication, the coordination among multiple BSs and their multiple antennas [5]–[7], such as coordinated multi-point (CoMP), might serve as a possible solution that enables dynamic coordination between BSs to guarantee good received signal strengths at the UEs. However, in current cellular network architectures, such a coordination of BSs is very limited. In the current architectures, control signaling for BS coordination needs to traverse the access network gateways and costly backhaul links, where the very high latency and limited transmission capacity among BSs can be the reasons for the infeasibility of BS coordination [8].

Software-defined networking (SDN) is introduced as a paradigm shift to solve the problems of hardware-based, closed, and inflexible network architectures. SDN efficiently creates centralized network abstraction with the provisioning of programmability over the entire network. SDN is used primarily for core (wired) networks and many papers have been published the last several years. Recently, SDN has been applied to wireless networks, called wireless SDN (W-SDN) [9]. The objectives of W-SDN are programmability, co-operativeness, virtualizability, openness, and visibility. One of the proposed W-SDN solutions for 5G systems is SoftAir [8], which enables an efficient coordination between remote radio heads (RRHs) via software-defined architecture.

In this paper, our objective is to solve the NLOS problem of millimeter-wave communication by using SoftAir architecture, and consequently facilitate ubiquitous millimeter-wave coverage by the newly introduced dynamic base station formation, which adaptively coordinates BSs and their multi-antennas to always satisfy the quality-of-service (QoS) requirements of UEs. As shown in Figure 1, SoftAir architecture using low-latency high-bandwidth fronthaul links to realize accu-

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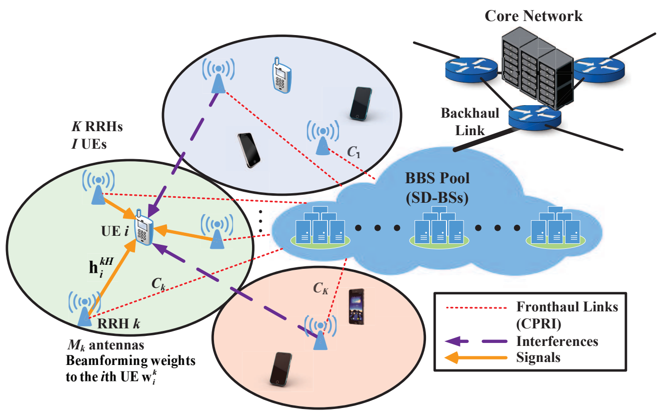


Fig. 1: Network architecture of SoftAir [8] for 5G millimeter-wave cellular systems.

rate, high-resolution synchronization among RRHs and enable flexible RRH coordinations. Moreover, we investigate the millimeter-wave channel model between UEs and RRHs to show the unique characteristics of millimeter-wave transmissions. The channel effects are studied with respect to three link-states: LOS, NLOS, or Outage. Further, we analyze the millimeter-wave coverage problem that jointly optimizes associations between RRHs and UEs as well as the beamforming weights of millimeter-wave RRHs. The objective function is how to maximize the achievable UE sum-rate while guaranteeing UEs' QoS requirements and system-level constraints with respect to (i) RRH-UE associations, (ii) fronthaul link capacity between the baseband server (BBS) pool and RRHs, and (iii) beamforming weights of RRHs.

We prove that the underlying coverage optimization problem with non-convex constraints is np-hard. Thus, we propose an iterative algorithm for dynamic BS formation to obtain optimal solutions in RRH-UE associations and beamforming vectors. By exploiting successive convex approximations [10], [11], we transform the original mixed-integer nonlinear programming (MINLP) of the coverage problem into a mixed-integer second-order cone programming (MISOCP). The final iterative convex programming is efficiently solved by commercial convex tool, i.e., CPLEX [12] or MOSEK [13]. Simulation results confirm that the proposed dynamic BS formation algorithm completely overcomes the NLOS problem, satisfies all UEs' QoS requirements, and outperforms conventional millimeter-wave association and suboptimal beamforming schemes. To the best of our knowledge, this work is the first to propose dynamic millimeter-wave base station formation through software-defined system design, which effectively optimizes UE sum-rate and achieves ubiquitous millimeter-wave communication coverage for 5G wireless systems.

The rest of the paper is organized as follows. Section II introduces the system model. Section III gives the problem formulation of millimeter-wave coverage. Section IV provides the proposed dynamic base station formation for ubiquitous millimeter-wave coverage. Section V presents the performance evaluation. Finally, Section VI concludes the paper.

II. System Model

In this section, we introduce 5G millimeter-wave communication system, which consists of software-defined cellular systems and millimeter-wave communication.

A. *Software-Defined Cellular System*

We consider a multi-user, multi-cell SoftAir [8] downlink system as in Figure 1. Specifically, SoftAir comprises three main parts: (i) the centralized BBS pool, which connects to the core network via backhaul links and consists of software-defined BSs (SD-BSs), (ii) RRHs equipped with antennas, which are remotely controlled by SD-BSs and serve UEs' transmissions, and (iii) low-latency high-bandwidth fronthaul links (fiber or microwave) using common public radio interface (CPRI) for an accurate, high-resolution synchronization among RRHs. Thus, SoftAir can provide accurate channel state information of the entire network to the BBS pool through the flexible design of SD-BSs and RRHs as well as control traffic forwarding technique [14], [15], and consequently enhance significantly the evolvability, scalability, and cooperativeness of distributed RANs.

As shown in Figure 1, let $\mathcal{K} = \{1, \ldots, K\}$ and $\mathcal{I} = \{1, \ldots, I\}$ denote the set of RRHs and UEs in the SoftAir system, respectively. We assume that the kth RRH ($k \in \mathcal{K}$) equips with M_k antennas and each UE has a single antenna. All the RRHs are connected to the BBS pool via the fronthaul links, where the kth link between the kth RRH and the pool has a predetermined capacity C_k. Suppose that each UE is served by a specific group of associated RRHs, and a RRH can serve multiple UEs at the same time. To express the association status between RRHs and UEs, we introduce the following binary variables as the indicators. In particular, while RRHs can be active to serve UEs or shutdown to save the energy consumption, $\{a_k, k \in \mathcal{K}\}$ denotes the activity of RRHs as

$$a_k = \begin{cases} 1, & \text{the } k\text{th RRH is in active mode;} \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

Also, $\{b_{ik}, i \in \mathcal{I}, k \in \mathcal{K}\}$ denotes the association between RRHs and UEs as

$$b_{ik} = \begin{cases} 1, & \text{the } i\text{th UE is served by the } k\text{th RRH;} \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

Furthermore, in order to characterize the group (cluster) serving of RRHs, the clustering indicators $\{N_{ik}, i \in \mathcal{I}, k \in \mathcal{K}\}$ are introduced as

$$N_{ik} = \begin{cases} 1, & (i,k) \in \mathcal{L}; \\ 0, & (i,k) \notin \mathcal{L}, \end{cases} \tag{3}$$

Notations: Throughout this paper, bold uppercase and lowercase letters denote matrices and vectors, respectively. $\mathbb{C}$ denotes the set of complex numbers. $\mathbb{E}[\cdot]$ and $\Pr[\cdot]$ denote the expectation and probability operator, respectively. x^*, $\Re\{x\}$, $\Im\{x\}$, and $|x|$ respectively represent the complex conjugate, real part, imaginary part, and absolute value of complex variable $x \in \mathbb{C}$. $\mathbf{x}^T$, $\mathbf{x}^H$, and $\|\mathbf{x}\|_2$ represent the transpose, Hermitian, and two-norm of vector $\mathbf{x}$, respectively.

where $\mathcal{L} = \{(i,k) | i \in \mathcal{I}, k \in \mathcal{N}_i\}$ denotes the predetermined set of feasible association and $\mathcal{N}_i$ denotes the set of near RRHs for the ith UE, which can be determined based on the distance or channel gain from RRHs to each UE. From these variable definitions, we can obtain the equality $a_k = 1 - \prod_{i=1}^{I}(1 - b_{ik}N_{ik}), \forall k \in \mathcal{K}$ and two sets of association constraints between RRHs and UEs as follows:

$$a_k \geq b_{ik}N_{ik}, \forall i \in \mathcal{I}, k \in \mathcal{K}; \quad (4)$$

$$\sum_{k=1}^{K} b_{ik}N_{ik} \geq 1, \forall i \in \mathcal{I}. \quad (5)$$

Eq. (4) implies that a RRH is in active mode if it is associated with at least one UE. Eq. (5) ensures that each UE is served by at least one RRH.

B. Millimeter-Wave Communication

In SoftAir downlink system, we introduce the precode vectors (i.e., beamforming weights) at RRHs that realize multi-antenna millimeter-wave transmissions from RRHs to UEs. Let $\mathbf{w}_i^k \in \mathbb{C}^{M_k \times 1}$ be the linear downlink beamforming vector at the kth RRH corresponding to the ith UE, $\mathbf{w}_i \triangleq [\mathbf{w}_i^{1T}, \ldots, \mathbf{w}_i^{KT}]^T \in \mathbb{C}^{M \times 1}$ with $M = \sum_{k \in \mathcal{K}} M_k$ be the set of beamforming vectors to the ith UE, and $\mathbf{W} \triangleq \{\mathbf{w}_1, \ldots, \mathbf{w}_I\} \in \mathbb{C}^{M \times I}$ be the network beamforming design. Let $s_i \in \mathbb{C}$ denote the signal intended for the ith UE with unit power (i.e., $\mathbb{E}[s_i^* s_i] = 1$.) Then, the kth RRH transmits the signal $\mathbf{x}_k = \sum_{i=1}^{I} \mathbf{w}_i^k s_i$ to UEs, and the ith UE receives the signal $y_i \in \mathbb{C}$ as

$$y_i = \sum_{k=1}^{K} \mathbf{h}_i^{kH} \mathbf{x}_k + \eta_i = \mathbf{h}_i^H \mathbf{w}_i s_i + \sum_{j=1, \neq i}^{I} \mathbf{h}_i^H \mathbf{w}_j s_j + \eta_i \quad (6)$$

where $\mathbf{h}_i \triangleq [\mathbf{h}_i^{1T}, \ldots, \mathbf{h}_i^{KT}]^T \in \mathbb{C}^{M \times 1}$, $\mathbf{h}_i^k \in \mathbb{C}^{M_k \times 1}$ denotes the channel coefficient vector from the kth RRH to the ith UE, and $\eta_i \sim \mathcal{CN}(0, \sigma^2)$ is the zero-mean circularly symmetric Gaussian noise with the noise power σ^2.

Different from conventional microwave communication, millimeter-wave transmissions have the following special characteristics: short-range communication, inevitable blockage effects, and sparse-scattering radio patterns [3], [7]. These jointly affect the downlink channel modeling (more specifically, channel coefficient vectors from RRHs to UEs) and necessitate the rigid analysis of (i) LOS, NLOS transmissions (i.e., blockage) as well as (ii) directional beams (i.e., the directivity). Specifically, we model the channel vector $\mathbf{h}_i^k$ as

$$\mathbf{h}_i^k = \left(l_i^k D_i^k \mathbf{\Phi}_i^k\right)^{1/2} \xi_i^k \in \mathbb{C}^{M_k \times 1} \quad (7)$$

where l_i^k is the large-scale path loss in power (which might also include lognormal shadowing), D_i^k is the directivity gain at the ith UE, $\mathbf{\Phi}_i^k \in \mathbb{C}^{M_k \times M_k}$ is the covariance matrix for antenna correlations in small-scale fading, and $\xi_i^k \sim \mathcal{CN}(\mathbf{0}, \mathbf{I}_{M_k})$ is the fast-fading channel vector.

We further investigate the millimeter-wave channel effects in Eq. (7) with respect to the feasible blockage information. Specifically, if the obstacles (e.g., buildings, vehicles, tree branches, foliage) are well understood in the geographic area, the transmissions between each RRH-UE pair can be categorized into one of the three link-states: LOS, NLOS, or Outage. First, a LOS state occurs when there is no blockage between the RRH and the UE. Assume that in each LOS link, there is no beamforming alignment errors (e.g., the RRH and the UE estimate the angles of arrival and adjust their antenna steering orientations accordingly), and the covariance matrix $\mathbf{\Phi}$ has rank one for all RRH antennas (due to few multi-paths for LOS millimeter-wave channels). This implies that for the LOS link between the kth RRH and the ith UE, the eigenvalue decomposition of the covariance matrix can be modeled as $\mathbf{\Phi}_i^k = M_k \mathbf{u}_i^k \mathbf{u}_i^{kH}$ with a unit vector $\mathbf{u}_i^k \in \mathbb{C}^{M_k \times 1}$. We model the corresponding channel vector as

$$\{\mathbf{h}_i^k; \text{LOS link}\} = \sqrt{M_k l_{iL}^k}\, \mathbf{u}_i^k \quad (8)$$

where l_{iL}^k is the path-loss modeling for a LOS link. Second, a NLOS state occurs when the RRH-UE link is blocked, and the covariance matrix in a NLOS link is similar to the case for microwave communication. We then model the NLOS channel vector as

$$\{\mathbf{h}_i^k; \text{NLOS link}\} = \left(l_{iN}^k \mathbf{\Phi}_i^k\right)^{1/2} \xi_i^k \quad (9)$$

where l_{iN}^k is the path-loss modeling for a NLOS link. Third, an outage state occurs when no millimeter-wave communication link can be established as the path loss between the RRH and the UE is so high [16]. In practice, this outage implies the case when the path loss in either a LOS or a NLOS state is sufficiently large, and it is a more accurate modeling at millimeter-wave frequency from experimental results [3]. In particular, we have the outage channel vector as

$$\{\mathbf{h}_i^k; \text{Outage link}\} = \mathbf{0}^{M_k \times 1}. \quad (10)$$

Finally, we formulate the path loss with respect to these three states for the link between the kth RRH and the ith UE as

$$\begin{aligned} l_{iL}^k &= (\alpha_L d_i^k)^{-\beta_L}; \\ l_{iN}^k &= (\alpha_N d_i^k)^{-\beta_N}; \\ l_{iO}^k &= 0, \end{aligned} \quad (11)$$

where d_i^k denotes the RRH-UE distance, α_L (α_N) can be interpreted as the path loss of the LOS (NLOS) link at a 1 [m] distance, and β_L (β_N) denotes the path-loss exponent of the LOS (NLOS) link. From experimental results, β_N value (can be up to 4) is normally much higher than β_L value (i.e., 2).

When the random, unknown deployment of blocking objects or statistical experiment measurements are considered (i.e., the blockage information is not entirely feasible), the stochastic geometry analysis can be exploited for millimeter-wave channel vector modeling [7]. Specifically, in this case, we model the channel vector as $\mathbf{h}_i^k = \left(l_i^k \mathbf{\Phi}_i^k\right)^{1/2} \xi_i^k$ (without the knowledge of directivity) and the corresponding path-loss

TABLE I: Path-loss models for three-state link and the occurred probabilities of LOS, NLOS, and outage states from the experimental data in [3], [16].

Carrier frequency	Path-loss models (three-state link) Eqs. (11)-(12)	Path-loss models (three-state link) and lognormal shadowing Eqs. (11)-(12)	LOS-NLOS-outage probability Eq. (13)
28 GHz	$\alpha_L = 10^{\frac{61.4}{20}}$, $\beta_L = 2$ $\alpha_N = 10^{\frac{72}{29.2}}$, $\beta_N = 2.92$	$\alpha_L = 10^{\frac{61.4+\zeta_L}{20}}$, $\beta_L = 2$, ζ_L[dB] $\sim \mathcal{N}(0, 5.8^2)$ $\alpha_N = 10^{\frac{72+\zeta_N}{29.2}}$, $\beta_N = 2.92$, ζ_N[dB] $\sim \mathcal{N}(0, 8.7^2)$	$\gamma_L = 1$, $\delta_L = 1/67.1$ $\gamma_O = \exp(5.2)$, $\delta_O = 1/30$
73 GHz	$\alpha_L = 10^{\frac{69.8}{20}}$, $\beta_L = 2$ $\alpha_N = 10^{\frac{82.7}{26.9}}$, $\beta_N = 2.69$	$\alpha_L = 10^{\frac{69.8+\zeta_L}{20}}$, $\beta_L = 2$, ζ_L[dB] $\sim \mathcal{N}(0, 5.8^2)$ $\alpha_N = 10^{\frac{82.7+\zeta_N}{26.9}}$, $\beta_N = 2.69$, ζ_N[dB] $\sim \mathcal{N}(0, 7.7^2)$	

component as

$$
\begin{aligned}
l_i^k =& \mathbf{1}[U < p_L(d_i^k)] l_{iL}^k \\
&+ \mathbf{1}[p_L(d_i^k) \leq U < (p_L(d_i^k) + p_N(d_i^k))] l_{iN}^k \\
&+ \mathbf{1}[(p_L(d_i^k) + p_N(d_i^k)) \leq U \leq 1] l_{iO}^k
\end{aligned} \tag{12}
$$

where $\mathbf{1}[\cdot]$ is the indicator function, $U \in [0, 1]$ is a uniform random variable, and the occurred probabilities of LOS, NLOS, and outage states is respectively formulated as [16]

$$
\begin{aligned}
p_L(d_i^k) =& (1 - p_O(d_i^k)) \gamma_L e^{-\delta_L d_i^k}; \\
p_N(d_i^k) =& (1 - p_O(d_i^k))(1 - \gamma_L e^{-\delta_L d_i^k}); \\
p_O(d_i^k) =& \max(0, 1 - \gamma_O e^{-\delta_O d_i^k}).
\end{aligned} \tag{13}
$$

γ_L (γ_O) and δ_L (δ_O) are parameters that depend on the propagation scenario and on the considered carrier frequency. TABLE I summarizes the parameter values used in the path loss and the occurred probability of three-state modeling.

III. Problem Formulation for Ubiquitous Millimeter-Wave Coverage

In this section, our objective is to efficiently realize ubiquitous millimeter-wave coverage of RRHs that supports satisfactory received signal strengths to all geo-distributed UEs. Specifically, we jointly optimize associations betweens RRHs and UEs and beamforming weights of RRHs so that the UE sum-rate is maximized, and UEs' QoS requirements and system-level constraints are satisfied simultaneously. This implies that the degradation of signal strengths due to NLOS transmissions can be completely solved by the solutions of the coverage optimization problem, particularly when the dense RRH deployment is considered. In the following, we first investigate the constraints with respect to (i) QoS requirements, (ii) beamforming weights, and (iii) fronthaul capacity. Combining these with the association constraints from Section II-A, we then formulate the ubiquitous millimeter-wave coverage problem.

A. UEs' QoS Requirements

Based on the channel modeling of millimeter-wave communication in Section II-B, we formulate the QoS requirements of UEs according to the associated SINR derivations. Let $\bar{\gamma_i}(\mathbf{W})$ and γ_i^{min} denote the received SINR and the minimum SINR requirement of the ith UE, respectively. Following the study in [17, Theorem 1], the SINR constraints of UEs can be formulated as $\forall i \in \mathcal{I}$,

$$
\bar{\gamma_i}(\mathbf{W}) = \frac{|\mathbb{E}[\mathbf{h}_i^H \mathbf{w}_i]|^2}{\sigma^2 + \mathrm{var}[\mathbf{h}_i^H \mathbf{w}_i] + \sum_{j=1,\neq i}^{I} \mathbb{E}[|\mathbf{h}_i^H \mathbf{w}_j|^2]} \geq \gamma_i^{min}. \tag{14}
$$

Moreover, when only LOS transmissions (without shadowing) are concerned for the ith UE, the corresponding deterministic channel effects can further simplify the SINR of the UE as

$$
\gamma_i(\mathbf{W}) = \frac{|\mathbf{h}_i^H \mathbf{w}_i|^2}{\sum_{j=1,\neq i}^{I} |\mathbf{h}_i^H \mathbf{w}_j|^2 + \sigma^2}. \tag{15}
$$

B. Beamforming Weights of RRHs

Given $\{s_i, \forall i \in \mathcal{I}\}$ and $\mathbf{w}_i^k$ as UEs' signals with unit power and the precoding vector at the kth RRH for the ith UE's signal, respectively, the transmit power used by this RRH to server the UE is $\mathbf{w}_i^{kH} \mathbf{w}_i^k$. Let P_k^{max} denote the maximum power of the kth RRH. We impose the constraints on beamforming weights of RRHs as follows:

$$
\sum_{i=1}^{I} \mathbf{w}_i^{kH} \mathbf{w}_i^k \leq a_k P_k^{max}, \forall k \in \mathcal{K}; \tag{16}
$$

$$
\mathbf{w}_i^{kH} \mathbf{w}_i^k \leq b_{ik} N_{ik} P_k^{max}, \forall i \in \mathcal{I}, k \in \mathcal{K}, \tag{17}
$$

where Eq. (16) limits the total transmit power of RRHs and Eq. (17) ensures that the transmit power from the kth RRH to the ith UE is set to zero if there is no association between them. Furthermore, as the predetermined set $\mathcal{L}$ shows the feasible associations between RRHs and UEs in Eq. (3), the complexity of computing precoding vectors can be significantly reduced by imposing additional transmit power constraints with respect to RRH-UE association [18]. Specifically, by only allowing RRH-UE links in $\mathcal{L}$, we set the beamforming weights of millimeter-wave communication links as

$$
\mathbf{w}_i^{kH} \mathbf{w}_i^k = 0 \text{ if } N_{ik} = 0, \forall i \in \mathcal{I}, k \in \mathcal{K}. \tag{18}
$$

Note that Eq. (18) reduces all possible RRH-UE links from IK between K RRHs and I UEs to $|\mathcal{L}|$ links (given that $|\mathcal{L}| << IK$), which in turns dramatically shrinks the possible solution sets of precoding vectors for lower computation complexity.

C. Fronthaul Capacity With RRH-UE Associations

In SoftAir, the BBS pool directly forwards the compressed precoding vectors and UEs' data streams to the corresponding RRHs; RRHs then precode the baseband signals and transmit to UEs. Specifically, after the BBS pool optimally determines the beamforming vector $\mathbf{w}_i$ for the ith UE, only nonzero weights in $\mathbf{w}_i$ are actually forwarded to the RRHs through the corresponding fronthaul links. More specifically, $\mathbf{w}_i^{kH}\mathbf{w}_i^k = 0$ implies that the kth RRH does not serve the ith UE, and the data stream of the ith UE is not routed from the BBS pool to the kth RRH (via the kth fronthaul link). Given the received SINR of the ith UE $\bar{\gamma}_i(\mathbf{W})$ from RRHs in Eq. (14), we can formulate the corresponding ergodic achievable data rate for the UE as

$$R_i(\mathbf{W}) = B(1-\kappa)\log_2\left(1+\bar{\gamma}_i(\mathbf{W})\right), \tag{19}$$

where B denotes the wireless transmission bandwidth and κ accounts for the spectral efficiency loss due to signaling at RRHs. By neglecting the fronthaul capacity consumption for transferring compressed beamforming vector (as compared to major consumption for data streams) and considering the RRH-UE associations in Eqs. (2)-(3), the per-fronthaul capacity constraints are formulated as

$$\sum_{i=1}^{I} b_{ik}N_{ik}R_i(\mathbf{W}) \leq C_k, \forall k \in \mathcal{K}. \tag{20}$$

This indicates that the total data rate transmitted at the kth RRH should be less than or equal to the rate forwarded by the kth fronthaul link.

D. Optimization Problem of the Millimeter-Wave Coverage

So far, we have successfully characterized the QoS and system-level constraints for the millimeter-wave coverage problem. To further realize a spectral-efficient coverage design, we aim to maximize the total achievable data rates at UEs as the objective function of the optimization problem. Specifically, given R_i in Eq. (19) as the ergodic achievable rate of the ith UE, the UE sum-rate is provided as $\sum_{i=1}^{I} R_i$; hence, we define the millimeter-wave coverage problem in software-defined millimeter-wave systems as follows.

Definition 1: **[Ubiquitous Millimeter-Wave Coverage Problem.]** Given a software-defined millimeter-wave system with the RRH set $\mathcal{K}$ and the UE set $\mathcal{I}$, and the precoding matrix $\mathbf{W}$, the millimeter-wave coverage optimization problem is

$$\begin{array}{cc} \textbf{Find:} & a_k \in \{0,1\}, b_{ik} \in \{0,1\}, \mathbf{w}_i^k, \forall i \in \mathcal{I}, k \in \mathcal{K} \\ \textbf{Maximize} & \sum_{i=1}^{I} R_i(\mathbf{W}) \\ \textbf{Subject to} & (4),(5),(14),(16),(17),(18),(20) \end{array} \tag{21}$$

IV. Dynamic Base Station Formation via Successive Convex Approximation

Aiming to solve the millimeter-wave coverage problem, in this section, we propose a dynamic base station (i.e., RRHs) formation that optimally determines the following: (i) the association assignments between RRHs and UEs; (ii) the corresponding beamforming weights of millimeter-wave RRHs. In particular, we first prove that the millimeter-wave coverage problem is np-hard. Next, by showing that this coverage problem belongs to mixed-integer nonlinear programming (MINLP) [11], we propose an iterative algorithm of the dynamic BS formation that yields feasible optimal solutions by exploiting convex approximation technique.

A. NP-Hardness of Millimeter-Wave Coverage Problem

With the millimeter-wave coverage problem in Definition 1, the corresponding *decision step* of the problem is introduced in the following Definition 2.

Definition 2 (Decision step L of millimeter-wave coverage problem) *Given a RRH set $\mathcal{K}$, a UE set $\mathcal{I}$, a positive constant z, and a positive integer c, the decision step L of the millimeter-wave coverage problem determines whether there exists a RRH subset $\mathcal{K}' \subseteq \mathcal{K}$ with $\sum_{i=1}^{I} R_i(\mathbf{w}_i^k|_{i\in\mathcal{I},k\in\mathcal{K}'}) = z$, and $\sum_{k\in\mathcal{K}'} a_k = c$ such that for each UE $i \in \mathcal{I}$ (i) there exists at least one RRH $k \in \mathcal{K}'$ for $b_{ik}N_{ik} = 1$ and (ii) the QoS requirement is satisfied (i.e., $\mathcal{U}(\bar{\gamma}_i - \gamma_i^{min}) = 1$ where $\mathcal{U}(\cdot)$ is a step function), and for each RRH $k \in \mathcal{K}'$ (iii) the beamforming weight constraints and (iv) the fronthaul constraint are met (i.e., $\mathcal{U}(a_kP_k^{max} - \sum_{i=1}^{I}\mathbf{w}_i^{kH}\mathbf{w}_i^k) + \sum_{i=1}^{I}\mathcal{U}(b_{ik}NikP_k^{max} - \mathbf{w}_i^{kH}\mathbf{w}_i^k) + \mathcal{U}(C_k - \sum_{i=1}^{I} b_{ik}N_{ik}R_i) = I+2$.)*

Theorem 1: The millimeter-wave coverage problem in Eq. (21) is np-hard.

Proof: First, we argue that the decision step L is an np problem. Given an instance of millimeter-wave coverage, a verification algorithm can effectively check whether each UE has at least one RRH in its cluster (i.e., within the link set $\mathcal{L}$ in Eq. (3) of the UE) and has its QoS requirement satisfied, whether the beamforming weight constraints, the fronthaul constraint of each RRH are met, and whether $\sum_{i=1}^{I} R_i = z$ and $\sum_{k\in\mathcal{K}} a_k = c$. Hence, the decision-step $L \in$ NP.

Next, we show that the minimum dominating set (MDS) problem [19], which is np-complete, can be reduced to the considered decision step (i.e., MDS $\leq_P$ L.) in polynomial time. An instance of MDS is given by a RRH set $\bar{\mathcal{K}}$, a UE set $\bar{\mathcal{I}}$, a positive constant $\bar{z}$, and a positive integer $c-1$. The objective of MDS is to determine whether there is such a dominating set $\bar{\mathcal{K}}' \subseteq \bar{\mathcal{K}}$ that $\sum_{k\in\bar{\mathcal{K}}'}\mathcal{U}(a_kP_k^{max} - \sum_{i\in\bar{\mathcal{I}}}\mathbf{w}_i^{kH}\mathbf{w}_i^k) = \sum_{k\in\bar{\mathcal{K}}'}\mathcal{U}(I - \sum_{i=1}^{I}\mathcal{U}(b_{ik}NikP_k^{max} - \mathbf{w}_i^{kH}\mathbf{w}_i^k)) = \sum_{k\in\bar{\mathcal{K}}'}\mathcal{U}(C_k - \sum_{i\in\bar{\mathcal{I}}} b_{ik}N_{ik}R_i) = c-1$, $\sum_{i\in\bar{\mathcal{I}}} R_i = \bar{z}$, and each UE $i \in \bar{\mathcal{I}}$ has at least one RRH $k \in \bar{\mathcal{K}}'$ in its cluster and has its QoS requirement met. Following the idea of MDS, we construct an instance of decision step L from the one of MDS as follows. The sets $\mathcal{K}$ and $\mathcal{I}$ and the positive constant z are defined as $\mathcal{K} = \bar{\mathcal{K}} \cup k'$, $\mathcal{I} = \bar{\mathcal{I}}$, and $z = \sum_{i\in\mathcal{I}} R_i(\mathbf{w}_i^k|_{i\in\mathcal{I},k\in\mathcal{K}})$, where k' is a new RRH element with $P_{k'}^{max} > \sum_{i\in\mathcal{I}}\mathbf{w}_i^{k'H}\mathbf{w}_i^{k'}$ and $C_{k'} > \sum_{i\in\mathcal{I}} R_i$, and is within the cluster of at least one element in $\bar{\mathcal{I}}$. The instance of decision step L is then obtained as sets $\mathcal{K}$, $\mathcal{I}$, a positive constant z, and a positive integer c.

We further prove that the original instance of MDS is a "yes instance" if and only if the created instance of decision step L is also a "yes instance". On the one hand, suppose the created instance of decision step L has a solution $\mathcal{K}' \subseteq \mathcal{K}$ with $\sum_{i\in\mathcal{I}} R_i(\mathbf{w}_i^k|_{i\in\mathcal{I},k\in\mathcal{K}'}) = z$ and $\sum_{k\in\mathcal{K}'} a_k = c$. By our construction, RRH k' is one of the most powerful RRHs within certain UEs' clusters and satisfies the beamforming weight constraint; thus k' should be included in $\mathcal{K}'$. This implies that RRH k' is the element of $\mathcal{K}'$ that satisfies fronthaul capacity constraint. Since $\bar{\mathcal{K}} = \mathcal{K} - k'$, the instance of MDS then has a dominating set $\bar{\mathcal{K}}' \subseteq \bar{\mathcal{K}}$ with $\sum_{i\in\bar{\mathcal{I}}} R_i(\mathbf{w}_i^k|_{i\in\bar{\mathcal{I}},k\in\bar{\mathcal{K}}'}) = \bar{z}$ and $\sum_{k\in\bar{\mathcal{K}}'} a_k = c-1$. On the other hand, suppose there is a dominating set $\bar{\mathcal{K}}' \subseteq \bar{\mathcal{K}}$ with $\sum_{i\in\bar{\mathcal{I}}} R_i(\mathbf{w}_i^k|_{i\in\bar{\mathcal{I}},k\in\bar{\mathcal{K}}'}) = \bar{z}$ and $\sum_{k\in\bar{\mathcal{K}}'} a_k = c-1$ in the original MDS instance. Through similar arguments, the minimum number of required RRHs is c and the positive constant is z in the constructed instance of decision step L. Thus, we have shown that MDS problem can be reduced to the decision step L by the proposed construction. As our construction takes polynomial time and $L \in$ NP, we conclude that the decision step L is np-complete. Since the coverage optimization problem in Eq. (21) has an np-complete decision step, the millimeter-wave coverage problem is np-hard [19]. ■

B. SCA-based Dynamic BS Formation

As shown above the millimeter-wave coverage problem is np-hard, this coverage problem is a MINLP problem. Specifically, since Eq. (20) is non-convex, the coverage problem in Eq. (21) is classified as a non-convex mixed integer programming. It implies that an optimal solution for this problem is very difficult to compute and that the solution would be of little practical interest even if it is possible to obtain. Hence, in this section, we transform the original coverage problem into a tractable formulation so that advanced optimization tools can be used for satisfactory solutions. In particular, we adopt the successive convex approximation (SCA) method [10], [11] to approximate non-convex continuous constraints (i.e., Eq. (20)) with series of second-order cone (SOC) constraints and arrive at a MISOCP problem, which can be solved by commercial tools, such as CPLEX [12] or MOSEK [13].

1) Successive Convex Approximation (SCA): First of all, given the power constraints in Eqs. (16)-(17), we can easily rewrite these hyperbolic constraints into MISOC forms as

$$\|[\mathbf{w}_1^{kT}, \ldots, \mathbf{w}_I^{kT}, \frac{a_k - P_k^{max}}{2}]^T\|_2 \le \frac{a_k + P_k^{max}}{2}, \forall k \in \mathcal{K}. \tag{22}$$

$$\|[\mathbf{w}_i^{kT}, \frac{b_{ik}N_{ik} - P_k^{max}}{2}]^T\|_2 \le \frac{b_{ik}N_{ik} + P_k^{max}}{2}, \forall i \in \mathcal{I}, k \in \mathcal{K}. \tag{23}$$

Next, due to the fact that $\mathrm{var}[\mathbf{h}_i^H\mathbf{w}_i] = \mathbb{E}[|\mathbf{h}_i^H\mathbf{w}_i|^2] - |\mathbb{E}[\mathbf{h}_i^H\mathbf{w}_i]|^2$, the constraints of QoS requirement in Eq. (14) can be transformed as

$$(1 + \frac{1}{\gamma_i^{min}})|\mathbb{E}[\mathbf{h}_i^H\mathbf{w}_i]|^2 \ge \sum_{j=1}^{I} \mathbb{E}[|\mathbf{h}_i^H\mathbf{w}_j|^2] + \sigma^2. \tag{24}$$

Similar to the consideration in [5], these beamforming vectors $\mathbf{w}_i^k, \forall i \in \mathcal{I}, k \in \mathcal{K}$ are phase-invariant, which implies that $\mathbf{w}_i^k$ is feasible for QoS requirements if and only if its rotated version $\mathbf{w}_i^k e^{\sqrt{-1}\theta_i^k}$ is. Combing this with the fact that $\mathbf{w}_i^k$ and $\mathbf{w}_i^k e^{\sqrt{-1}\theta_i^k}$ bring the same energy consumption in the objective function of the coverage problem in Eq. (21), we can rewrite the SINR constraints into the following SOC forms:

$$\sqrt{1 + \frac{1}{\gamma_i^{min}}}\mathfrak{Re}\{\mathbb{E}[\mathbf{h}_i^H\mathbf{w}_i]\} \ge \|[\sqrt{\mathbb{E}[|\mathbf{h}_i^H\mathbf{w}_1|^2]}, \ldots, \sqrt{\mathbb{E}[|\mathbf{h}_i^H\mathbf{w}_I|^2]}, \sigma]\|_2, \forall i \in \mathcal{I}; \tag{25}$$

$$\mathfrak{Im}\{\mathbb{E}[\mathbf{h}_i^H\mathbf{w}_i]\} = 0, \forall i \in \mathcal{I}. \tag{26}$$

In particular, if the SINR constraints follow the deterministic channel effects (e.g., LOS transmission without considering shadowing) as in Eq. (15), the corresponding SOC forms can also be rewritten as $\sqrt{1 + \frac{1}{\gamma_i^{min}}}\mathfrak{Re}\{\mathbf{h}_i^H\mathbf{w}_i\} \ge \|[\mathbf{h}_i^H\mathbf{W}, \sigma]\|_2$ and $\mathfrak{Im}\{\mathbf{h}_i^H\mathbf{w}_i\} = 0$.

Finally, we employ SCA to approximate the non-convex fronthaul capacity constraint into a more tractable form. Specifically, Eq. (20) can be first transformed as

$$\sum_{i=1}^{I} b_{ik}N_{ik} \log_2 (1 + \bar{\gamma}_i(\mathbf{W}))^{B(1-\kappa)} \le C_k. \tag{27}$$

Then, by introducing a set of new variables $\{\alpha_{ik}, \beta_i, \delta_i; i \in \mathcal{I}, k \in \mathcal{K}\}$, we rewrite the capacity constraints into several related inequalities as follows:

$$\sum_{i=1}^{I} \alpha_{ik} \le C_k, \forall k \in \mathcal{K}; \tag{28a}$$

$$(b_{ik}N_{ik})^2 \le \alpha_{ik}\beta_i; \tag{28b}$$

$$\log_2 (1 + \delta_i)^{B(1-\kappa)} \le \frac{1}{\beta_i}; \tag{28c}$$

$$\frac{|\mathbb{E}[\mathbf{h}_i^H\mathbf{w}_i]|^2}{\sigma^2 + \mathrm{var}[\mathbf{h}_i^H\mathbf{w}_i] + \sum_{j=1,\ne i}^{I} \mathbb{E}[|\mathbf{h}_i^H\mathbf{w}_j|^2]} \le \delta_i, \tag{28d}$$

where inequalities in Eq. (28a) are in MISOC forms and Eq. (28b) comes from the fact that $(b_{ik}N_{ik})^2 = b_{ik}N_{ik}$. Following the similar approach in Eqs. (22)-(23), Eq. (28b) can be further rewritten into MISOC constraints as

$$\|[b_{ik}N_{ik}, \frac{\alpha_{ik} - \beta_i}{2}]\|_2 \le \frac{\alpha_{ik} + \beta_i}{2}, \forall i \in \mathcal{I}, k \in \mathcal{K}. \tag{29}$$

Furthermore, adopting similar procedures in [6], we apply the first-order Taylor series expansion as an iterative convex approximation with respect to Eq. (28c) and Eq. (28d) as follows. Specifically, by transforming Eq. (28c) into $1 + \delta_i \le 2^{\frac{1}{\beta_i B(1-\kappa)}}$ and approximating the exponential function around the $(t+1)$th updated point $\beta_i^{(t)}$, we can rewrite the inequalities in Eq. (28c) as the following series of SOC constraints:

$$1 + \delta_i \le \mathfrak{F}_i^{(t)}(\beta_i), \forall i \in \mathcal{I} \tag{30}$$

where $\mathfrak{F}_i^{(t)}(\beta_i) \triangleq 2^{\overline{\frac{1}{\beta_i^{(t)}B(1-\kappa)}}} - \frac{2^{\overline{\frac{1}{\beta_i^{(t)}B(1-\kappa)}}}}{(\beta_i^{(t)})^2 B(1-\kappa)}(\beta_i - \beta_i^{(t)})$. Moreover, by transforming Eq. (28d) into $|\mathbb{E}[\mathbf{h}_i^H\mathbf{w}_i]|^2 \le$

$(1-\frac{1}{\delta_i+1})(\sigma^2+\sum_{j=1}^{I}\mathbb{E}[|\mathbf{h}_i^H\mathbf{w}_j|^2])$, we approximate these non-convex constraints with another SOC series as

$$|\mathbb{E}[\mathbf{h}_i^H\mathbf{w}_i]|^2+\frac{|\mathbb{E}[\mathbf{h}_i^H\mathbf{w}_i]|^2}{\delta_i}\leq\mathfrak{G}_i^{(t)}(\mathbf{W}),\forall i\in\mathcal{I} \quad (31)$$

where $\mathfrak{G}_i^{(t)}(\mathbf{W}) \triangleq \sigma^2+\sum_{j=1}^{I}(2\mathfrak{Re}\{\mathbb{E}[\mathbf{w}_j^{(t)H}\mathbf{h}_i\mathbf{h}_i^H\mathbf{w}_j]\}-\mathbb{E}[|\mathbf{h}_i^H\mathbf{w}_j^{(t)}|^2])$. In particular, if the deterministic channel effects are considered, the corresponding formulation becomes $\frac{|\mathbf{h}_i^H\mathbf{w}_i|^2}{\delta_i}\leq\sigma^2+\sum_{j=1,\neq i}^{I}(2\mathfrak{Re}\{\mathbf{w}_j^{(t)H}\mathbf{h}_i\mathbf{h}_i^H\mathbf{w}_j\}-|\mathbf{h}_i^H\mathbf{w}_j^{(t)}|^2)$. Combining these with the *monotonicity* of logarithmic function and $\delta_i\geq 0$, we can approximate the non-convex coverage problem in Eq. (21) at iteration $t+1$ by the following upper-bounded convex programming with Eqs. (30)-(31) as

$$\begin{array}{ll}\textbf{Find:} & a_k, b_{ik}, \mathbf{w}_i^k, \alpha_{ik}, \beta_i, \delta_i, \forall i\in\mathcal{I}, k\in\mathcal{K}\\ \textbf{Maximize} & \prod_{i=1}^{I}(1+\delta_i)^{B(1-\kappa)}\\ \textbf{Subject to} & (4),(5),(18),(22),(23),(25),\\ & (26),(28a),(29),(30),(31)\\ & a_k\in\{0,1\}, b_{ik}\in\{0,1\},\forall i\in\mathcal{I},k\in\mathcal{K}\end{array} \quad (32)$$

Note that as the objective and all constraint functions in Eq. (32) follow SOC representation, Eq. (32) becomes a mixed-integer second-order cone programming (MISOCP) problem. This implies that at each iteration, Eq. (32) can be optimally solved through standard MISOCP tools as mentioned. Algorithm 1 summarizes the proposed iterative algorithm.

Algorithm 1: SCA-based Dynamic BS Formation

initialize $\beta^{(0)}$ and $\mathbf{W}^{(0)}$;
set $t=0$;
repeat
  solve the MISOCP problem in Eq. (32) with $\beta^{(t)}$ and $\mathbf{W}^{(t)}$ for optimal solution $\{\bar{\mathbf{w}}_i^k,\bar{a}_k,\bar{b}_{ik},\bar{\alpha}_{ik},\bar{\beta}_i,\bar{\delta}_i\}$;
  set $t:=t+1$;
  update $\beta^{(t)}=\bar{\beta}$ and $\mathbf{W}^{(t)}=\bar{\mathbf{W}}$;
until *convergence or the maximum number of iterations is reached*;

V. Performance Evaluation

In this section, we present simulation results to evaluate the performance achieved by the dynamic BS formation. Considering practical obstacles in 5G networks, we build software-defined millimeter-wave systems upon METIS [20], which aims to lay the 5G foundation for year 2020 and beyond with realistic consideration of different environments of buildings, roads, park, etc. As shown in Figure 2, the urban environmental model is established, based on observations regarding the city structure of Madrid, and captures more aspects than Manhattan grid. Following the deployment baseline of a three-sector macro station and 12 pico stations for network infrastructure [20], we design 13 RRHs with different specifications: RRH 1, indicated by magenta rectangles, mimics the powerful macro station and has four equipped antennas on the roof of building 6 with maximum transmit power 43 [dBm]; RRHs 2-13, indicated by blue stems to simulate pico stations, has two equipped antennas of 10 [m] height and maximum power 36 [dBm]. We further set the fronthaul capacity as 10 [bits/s/Hz] for each RRH and the carrier frequency as 28 [GHz], and all UEs are randomly-distributed in the street. The three-state path-loss model with lognormal shadowing is considered, and the thermal noise power is set as -101 [dBm/Hz].

A. Convergence Behavior of Dynamic BS Formation

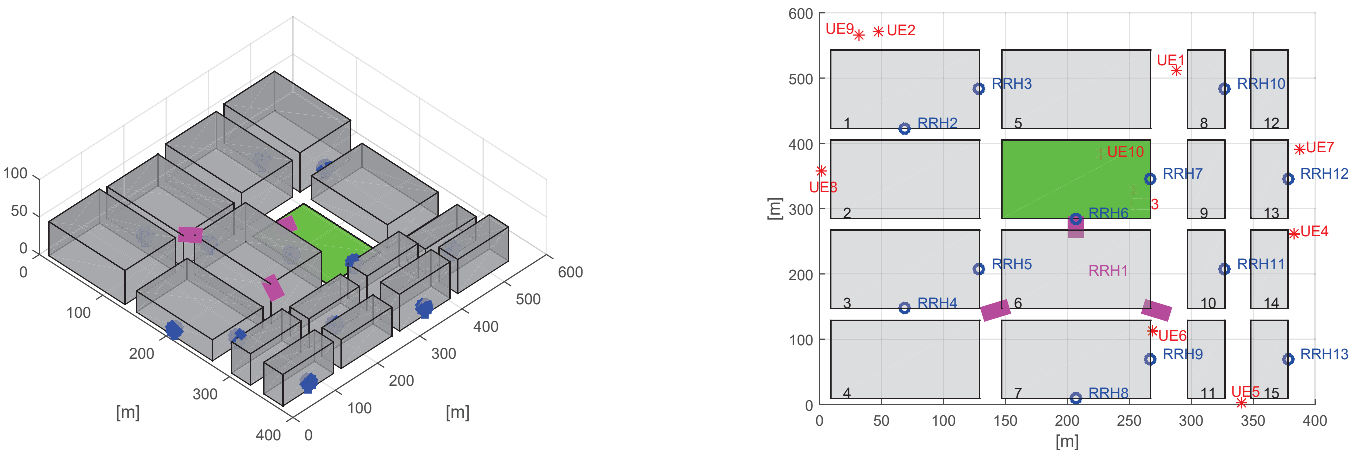
To illustrate the fast convergence of dynamic BS formation in Algorithm 1, Figure 3 shows the convergence behavior of downlink system sum-rate and the beamforming power of 7 selected millimeter-wave RRHs with 10 UEs randomly-distributed, where the required minimum SINR for each UE is γ_i^{min} =6 [dBW]. The results imply that by exploiting SCA, our proposed Algorithm 1 converges very fast after only 4 iterations, which serves as a desired stopping point. Moreover, with the maximum achievable sum-rate around 90 [bits/s/Hz], the average rate per UE can be easily achieved to 4.5 [Gbps], given 500 [MHz] transmission bandwidth from millimeter-wave communication. We demonstrate the efficiency of our proposed BS formation that quickly makes the decision for RRH-UE associations and beamforming weights, facilitating millimeter-wave coverage upon time-varying channels.

B. Performance Comparison of Dynamic BS Formation and Conventional Millimeter-wave Cell Association

As in [16], two schemes for cell association are commonly studied in conventional millimeter-wave communication.

- *Highest received power association:* Like in microwave communication, the UE-BS association is based on downlink reference signals, which undergo both path-loss and shadowing. Hence, a UE will be served by the BS providing the highest received power to it.
- *Smallest path-loss association:* As millimeter-wave communication has less slowly-varying shadowing due to pronounced blockage impact on received signals, UEs might be unable to consider random fluctuations by shadowing. Thus, in this case, a UE will be served by the BS with the smallest path-loss to it.

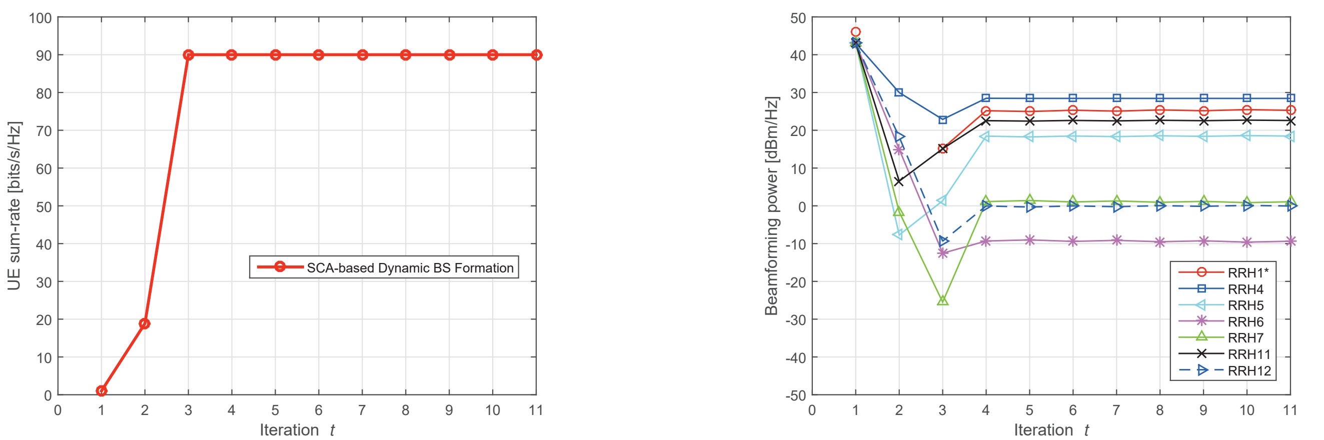
We evaluate the achievable sum-rates from Algorithm 1 and the above two schemes with respect to UEs' SINR requirements in Figure 4. To realize conventional association schemes, the matched filtering precoding method is exploited as $\mathbf{w}_i^k=\mathbf{h}_i^k/\|\mathbf{h}_i^k\|_2$, the transmit power is equally allocated among the UEs in the same BS's coverage, and the greedy algorithm is used for UE scheduling [21]. Figure 4 shows that the proposed dynamic BS formation significantly outperforms conventional millimeter-wave association with ubiquitous UE coverage and high data rates. This is because our solution accounts the global network conditions by centralized, software-defined system architecture and jointly optimizes the association and precoding decision. The decreasing data-rate trend of our solution is due to fixed-power concern of RRHs. On the other hand, classical solutions rather exploit static and suboptimal designs and thus barely support high UEs' SINR requirements. The results from the smallest path-loss and



(a) 3D visualization.

(b) 2D visualization with 10 randomly-distributed UEs.

Fig. 2: An urban environmental model of the Madrid grid from METIS [20] with 13 RRHs deployed.



(a) Convergence behavior of the UE sum-rate.

(b) Convergence of the beamforming power at 7 selected RRHs.

Fig. 3: Fast convergence of the dynamic BS formation in Algorithm 1.

the highest received power schemes have close performance. These confirm the efficacy of our solution to solve the NLOS problem and achieves ubiquitous millimeter-wave coverage.

C. Impact of UE Density

Figure 5 shows the achievable UE sum-rates by Algorithm 1 with respect to the UE density. Specifically, as the number of served UEs increases, both the sum-rates and the average rate per UE decrease, due to lower signal power for the UEs sharing same RRHs' power resources and increasing downlink interferences. Moreover, while the achievable data rate per UE decreases with the increasing UE number, the dynamic BS formation can always support each UE with at least 500 [Mbps] rate through millimeter-wave transmissions, meeting the high data-rate requirements in 5G. The above results validate the adaptiveness of dynamic BS formation, which can be used for the design of 5G millimeter-wave communication.

VI. Conclusion

In this paper, through W-SDN SoftAir architecture, we develop a dynamic BS formation that achieves a joint optimal design of RRH-UE associations and beamforming weights of millimeter-wave RRHs to facilitate ubiquitous millimeter-wave coverage. The coverage optimization as a MINLP problem is proved to be np-hard; an iterative algorithm of the dynamic BS formation is proposed through SCA to yield optimal solutions. Simulations show that our solution can always satisfy UEs' QoS requirements with millimeter-wave transmissions and significantly outperforms conventional association schemes with suboptimal beamforming. Our solution can be used to solve the NLOS problem in 5G millimeter-wave systems.

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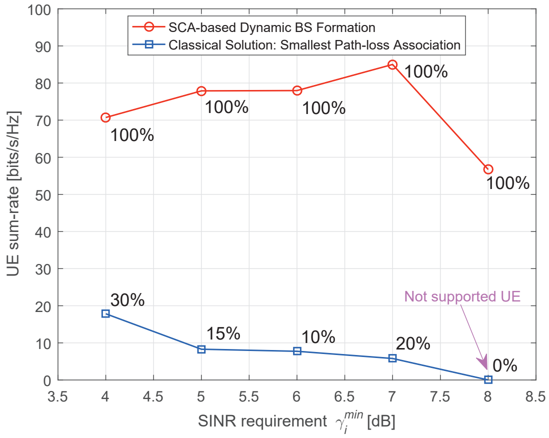
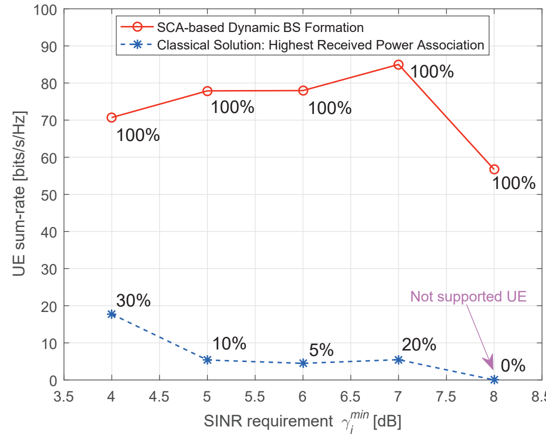


(a) Comparison with the smallest path-loss association.



(b) Comparison with the highest received power association.

Fig. 4: UE sum-rates achieved by the proposed dynamic BS formation and two conventional millimeter-wave association schemes, with respect to UEs' SINR requirements. The percentage shows the ratio of supported UEs to total UEs.

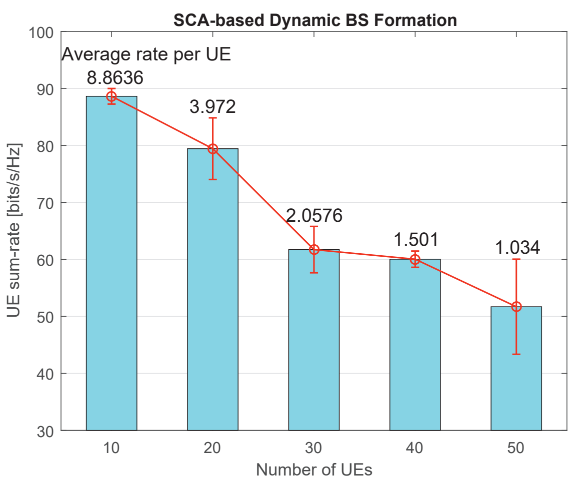


Fig. 5: Achievable UE sum-rates by the dynamic BS formation with respect to increasing UEs.

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