Joint Uplink–Downlink Capacity and Coverage Optimization via Site-Specific Learning of Antenna Settings

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Abstract—We propose a novel framework for optimizing antenna parameter settings in a heterogeneous cellular network. We formulate an optimization problem for both coverage and capacity – in both the downlink (DL) and uplink (UL) – which configures the tilt angle, vertical half-power beamwidth (HPBW), and horizontal HPBW of each cell’s antenna array across the network. The novel data-driven framework proposed for this nonconvex problem, inspired by Bayesian optimization (BO) and differential evolution algorithms, is sample-efficient and converges quickly, while being scalable to large networks. By jointly optimizing DL and UL performance, we take into account the different signal power and interference characteristics of these two links, allowing a graceful trade-off between coverage and capacity in each one. Our experiments on a state-of-the-art 5G NR cellular system-level simulator developed by AT&T Labs show that the proposed algorithm consistently and significantly outperforms the 3GPP default settings, random search, and conventional BO. In one realistic setting, and compared to conventional BO, our approach increases the average sum-log-rate by over 60% while decreasing the outage probability by over 80%. Compared to the 3GPP default settings, the gains from our approach are considerably larger. The results also indicate that the practically important combination of DL throughput and UL coverage can be greatly improved by joint UL-DL optimization.

Index Terms—Coverage and capacity optimization, Bayesian optimization, evolutionary computing, machine learning, antenna parameter optimization, uplink (UL), downlink (DL).

I. INTRODUCTION

A. Motivation

Cellular system capacity and coverage are strongly influenced by the base station (BS) antenna settings across the network. The shape and direction of the dominant beams, which are typically tuned by adjusting parameters such as downtilt angle, vertical half-power beamwidth (HPBW), and horizontal HPBW, play a critical role in increasing received signal strength over key areas of the cell and minimizing interference to neighboring cells. This process, known as cell shaping, is a periodic cell-specific optimization in response to changes in the distribution of user equipments (UEs) and other long-term network factors, aiming to optimize the coverage and capacity of a cellular network by shaping the coverage area of the cell in a way that closely matches the UE distribution.

The optimization of antenna parameters across a network is nontrivial because the settings across each cell are coupled by the interference, rendering the multicell optimization problem nonconvex and NP-hard [2]. Another challenge stems from the conflicting nature of the two key objectives, maximizing both coverage probability – which in practice means directing energy towards the cell edges at the expense of other-cell interference – and the sum or more often sum-log capacity, which tends to favor cell interior users with high SINR.

In the Third Generation Partnership Project (3GPP), global optimization methods based on stochastic system simulation are utilized to optimize parameter settings. Since the network models are usually small homogeneous hexagonal layouts, exhaustive search techniques can be used, resulting in typical fixed values that are the same for all cells, e.g., 12° downtilt angles [3]. In a real network, the antenna parameters can be designed using site-specific radio frequency planning tools, and any updates rely on trial-and-error methods based on field measurements over a long time period. These methods are neither scalable nor near-optimal, and hence there is a need for practical and automated optimization approaches that are well-supported by theory and utilize recent advances in data-driven design. This paper proposes such a framework.

Adding further complexity to antenna parameter optimization is balancing the uplink (UL) and downlink (DL) performance, which has rarely been considered. The optimal DL antenna parameters are generally suboptimal for the UL due to the major signal power and interference asymmetries between two links. The DL interference is dictated by the fixed locations of BSs, which transmit nearly continuously using high-gain antennas, while in the UL, mobile UEs, each of which transmits sporadically and (usually) omnidirectionally, generate the interference. Furthermore, large transmit

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power disparities exist between different types of BSs in a heterogeneous network (HetNet), resulting in coverage area differences, whereas UEs transmit at relatively low power, with location-dependent power control, amplifying the difference between the interference characteristics of the UL and the DL [4], [5].

B. Prior Work

The antenna parameter-based coverage and capacity optimization (CCO) literature has focused on DL optimization: UL optimization has received very little attention. Given the importance of UL coverage even for DL-centric data traffic – DL transmissions are not possible without reliable UL control channels – it is clear that UL coverage in particular should be considered when optimizing the antenna settings. Despite this, to the best of our knowledge, [6] is the only work in the literature that considers joint UL and DL antenna parameter-based CCO. They consider only downtilt under sparse system knowledge, however, and their descent-like search approach can only optimize a single network parameter.

Various studies parameterized by the key antenna parameters including downtilt [7], [8], [9], [10], [11], azimuth [12], [13], HPBW [13], [14], and transmit power [9], [15] have been conducted on downlink-only CCO. They have mainly focused on intelligent networks after the introduction of self-organizing network functionalities in 4G networks [16]. Among these works, [9], [10], [11], [12], [13] use traditional optimization and rule-based approaches, which are poor at adapting to different environments and thus require manual intervention. The inherent nonconvexity and complexity of the problem pose significant challenges for these approaches, which become increasingly complex and ineffective as the network size and complexity increase. On the other hand, [7], [8], [15] combine rule-based fuzzy systems with reinforcement learning (RL) for a more adaptive implementation. However, this fuzzy RL method also struggles to handle continuous or high-dimensional network configurations and leads to a complicated process for determining the reward signal for each state-action pair, due to the activation of multiple fuzzy membership functions [7].

More recent methods that have been used for antenna tuning are RL [17], [18], [19], [20], [21] and Bayesian optimization (BO) [19]. RL superficially may seem to be a suitable approach for CCO with its ability to adapt to changing environmental dynamics. However, RL methods need a very large amount of data to achieve high accuracy and tend to have slow convergence, resulting in extensive computations and long-lasting simulations [22], a fact we have encountered in our own studies over the last few years. RL also lacks safe exploration as random (e.g., epsilon-greedy) exploration can result in undesirable antenna parameters being tested which significantly degrades the system performance. Furthermore, it is not advisable or even possible to make large sudden changes in the parameters, especially the tilt angle. Alternatively, if just small incremental changes are allowed at each iteration, it further slows convergence, and often results in converging to a local optima far below the global optima.

BO is a more promising approach for the CCO problem, and it can speed up convergence and provide safe exploration [23]. In [19], the deep deterministic policy gradient algorithm (DDPG), an RL method, was compared with BO for optimizing network coverage and capacity, and it was shown that BO improves sample efficiency by over two orders of magnitude relative to DDPG. However, neither of these two approaches scales well with network size. BO suffers from cubic computational complexity, which limits its applications to low-dimensional problems. It decides on the next sampling point with a so-called acquisition function, and this requires solving a nonconvex problem with increasing computational cost as the training data size increases at each iteration [23]. This also makes choosing a proper acquisition function a challenging task in the implementation of BO as it has a major impact on its performance.

C. Contributions

We investigate the joint uplink and downlink antenna parameter optimization problem as a means of cell shaping and propose a data-driven method for fast site-specific optimization of capacity and coverage. The proposed novel algorithm leverages several key aspects of both Bayesian optimization (BO) and differential evolution (DE) and has several practically desirable properties which we now enumerate.

- **Sample- and time-efficient novel algorithm.** Our proposed approach is inspired by BO’s probabilistic model-building, which we combine with an evolutionary algorithm to quickly search and prune the space of candidate solutions. This is a sample- and time-efficient framework, improving sample efficiency by over two orders of magnitude compared to DDPG. Furthermore, our algorithm is demonstrated to have linear time complexity as opposed to cubic in BO.

- **Scalable to large network sizes.** Our approach gracefully scales to large networks with many cells and users while maintaining high accuracy and low complexity. We achieve this by utilizing a concept of a local neighborhood for each user, which includes cells with a strong measured reference signal received power (RSRP). By regressing the SINR of each user on the parameters of the selected cells before calculating a cumulative metric for optimization, we achieve greater prediction accuracy. This approach allows for centralized optimization without diminishing gains and massive overhead by eliminating the need to consider all interference links for every cell. Additionally, our approach enables each user to be modeled independently and in parallel, preserving the time efficiency of the algorithm.

- **Uplink and downlink joint optimization.** Our algorithm jointly optimizes the UL and DL of a multicell system and allows a trade-off between their importance, as well as, between coverage and capacity in each direction. We prioritize data rate in the DL and coverage in the UL by adjusting the trade-off coefficient accordingly. Our analysis shows that the joint UL and DL optimization significantly outperforms the uplink-only optimization in terms of DL coverage and capacity, and surpasses the downlink-only optimization in terms of UL coverage and capacity. These findings underscore the importance of
jointly optimizing both links to achieve a well-balanced overall performance in wireless communication systems.

- **Validation on a high-fidelity system-level simulator.**

  We experimentally evaluate the performance of our proposed algorithm on a state-of-the-art wireless simulator developed by AT&T Labs by comparing it with three baselines: (i) the default settings in 3GPP, (ii) random search, and (iii) conventional BO. This powerful system-level simulator closely mimics a real-world network, and we use a layout based on the real locations of AT&T BSs to compare the algorithms in terms of sample and time efficiency, and three other performance metrics: (i) average sum-log-rate of the UEs, (ii) outage probability (i.e., the fraction of UEs with SINR value below a predefined threshold), and (iii) the SINR distribution for all UEs.

**D. Notation and Organization**

We use bold lower-case and upper-case symbols to denote vectors and matrices, respectively. $X^T$ denotes the transpose of a matrix $X$, and $x_i$ denotes the $i$-th instance of a vector $x$. The notations $\mathbb{R}^{1 \times d}$ and $\mathbb{R}^{1 \times d}$ are used to represent $d$-dimensional vector of real numbers and positive real numbers. $1_D$ denotes the $D$-dimensional vector of all ones, and $\mathbb{1}_A$ denotes the indicator function over set $A$.

The rest of the paper is organized as follows. A system model is described, and the optimization problem is formulated in Section II. The proposed framework is presented with the evaluation metrics in Section III. The simulation details are given in Section IV, followed by the optimization performance results and discussions for the single and joint direction optimization in Section V. Conclusions and future directions are provided in Section VI.

**II. SYSTEM MODEL AND PROBLEM FORMULATION**

**A. System Model**

We consider a two-tier HetNet cellular network model consisting of a total of $M$ cells. There are tower-mounted “macro” BSs with three sector antennas, which can be deployed on a conventional hexagonal grid or using actual deployment locations: we consider both cases, including a current AT&T network deployment. The second tier is small cell (i.e., “pico”) BSs which are randomly distributed within these layouts, adhering to a minimum distance (i.e., 10m) between them and the macro BSs. We consider $N \gg M$ uniformly distributed UEs that are associated with a single BS based on the maximum downlink RSRP, which in effect, corresponds to the BS with the minimum path loss (small cell biasing is not considered in this work). Most of the system parameters, including the transmit power and channel and path loss models, are derived from the 3GPP urban macro-cellular scenario described in [24] for a bandwidth of 10 MHz at a carrier frequency of 2 GHz.

The focus of this work is on cell shaping, which involves adjusting antenna parameters to shape the cell coverage area and steer the dominant beams toward the intended locations, while minimizing interference to neighboring cells. The aim of cell shaping is to optimize the coverage area of a specific cell to match the UE distribution in the area, thereby improving the overall coverage and capacity of the network. It is worth noting that this is a long-term cell-specific optimization approach and assumes a stationary distribution of UEs, which differs from the more frequent UE-specific optimization that takes into account rapid changes in traffic and UE mobility. As a result, the scope of this work does not cover UE-specific optimization or high mobility scenarios.

We utilize Wireless Next-Generation Simulator (WiNGS) developed by AT&T Labs to obtain realistic measurements of SINR which could be substituted with actual SINR measurements (and CQI feedback) in real-world implementations. After the parameters of each BS antenna are set, WiNGS simulates the entire network and provides SINR values averaged over both the temporal and spatial domain: specifically, for the RSRP/SINR measurement the channel is sampled every 100ms over a 1s time window. Section II-C details this SINR calculation, while Section II-D presents our coverage and capacity metrics that are derived from the simulated SINR measurements.

In summary, our system model corresponds closely to a medium-sized urban cellular 5G NR network with both macrocells and picocells, with all crucial aspects of the system carefully modeled using a state-of-the-art simulator that is used by AT&T. More of the numerical values and pertinent details of our model and WiNGS are provided in Section IV.

**B. Antenna Model**

In the defined HetNet, both BSs and UEs are equipped with a uniform linear array (ULA) antenna system. We characterize the BS antenna configurations by three parameters: downtilt angle $\theta$, vertical HPBW $\phi^v$, and horizontal HPBW $\phi^h$. As illustrated in Fig. 1, the downtilt angle is defined as the angle between the antenna boresight and the horizontal plane. The vertical HPBW is the angular range over which antenna gain is above half of the maximum gain in the vertical plane, while the horizontal HPBW specifies the same in the horizontal plane. The antenna gain for a particular horizontal, $\phi^h$, and vertical angle, $\theta$, can be expressed as [25]

$$A(\phi^h, \theta^v) = -\min \{ -[A_H(\phi^h) + A_V(\theta^v)] \}, 25 \} \text{ dB}, \quad (1)$$

![Fig. 1. Illustration of antenna downtilt angle, vertical half-power beamwidth (HPBW), and horizontal HPBW.](image-url)
The set of all UEs is denoted by $\mathcal{U}$, and $x$ represents a particular horizontal, vertical, and azimuth setting of the antenna array configurations in this paper. Additionally, we only consider the optimization of BS antenna array configurations in this work, and UE antenna array configuration is not subject to optimization. Hence, while the value of $A_{ij}^r$, $A_{ij}^t$, $A_{ij}^r$, $A_{ij}^t$, $P_{ij}$, and $P_{ij}$ remains fixed during downlink optimization, in the uplink optimization $A_{ij}^t$ is fixed. On the other hand, $A_{ij}^t$ in DL SINR and $A_{ij}^t$ in UL SINR calculations can be expressed as the antenna gain, $A(\phi^r, \phi^t)$, formulation in (1) for a particular horizontal, vertical and/or azimuth, $\phi^r$, $\phi^t$, and $\phi^h$.

### E. Optimization Problem Formulation

We now formulate our proposed capacity-coverage optimization problem. The objective is to select the three antenna parameters $-\theta^r$, $\phi^r$, and $\phi^h$ for each cell that maximizes an arbitrarily weighted combination of capacity and coverage for both the downlink and uplink. The problem is as follows.

\[
\begin{align*}
\max_{x=\{\theta, \phi^r, \phi^h\}} \quad & F_x = (1 - \alpha) f(\text{SINR}^{DL}(x)) + \alpha f(\text{SINR}^{UL}(x)) \\
\text{s.t.} \quad & \theta_m \in \left[\theta_m, \bar{\theta}_m\right], \\
& \phi^r_m \in \left[\phi^r_m, \bar{\phi}^r_m\right], \\
& \phi^h_m \in \left[\phi^h_m, \bar{\phi}^h_m\right], \\
& m = 1, \ldots, M,
\end{align*}
\]

where $A_H(\phi^r) = \min \left[12 \left(\frac{\phi^r}{\phi^h}\right)^2, 25\right]$ dB, (2) $A_V(\theta^r) = \min \left[12 \left(\theta^r - \theta^m\right)^2, 20\right]$ dB. (3)
where

\[
\begin{align}
 f(SINR^{DL}(x)) &= \beta^{DL}R^{DL} - (1 - \beta^{DL})\zeta^{DL}, \\
 f(SINR^{UL}(x)) &= \beta^{UL}R^{UL} - (1 - \beta^{UL})\zeta^{UL}.
\end{align}
\]  

Specifically, \( \theta_m \) is the downtilt angle, \( \phi^v_{m} \) is the vertical HPBW, and \( \phi^h_{m} \) is the horizontal HPBW of \( m \)-th cell, which yields the vector notation \( \theta = [\theta_1, \ldots, \theta_M] \in \mathbb{R}_+^{1 \times M} \), \( \phi^v = [\phi^v_1, \ldots, \phi^v_M] \in \mathbb{R}_+^{1 \times M} \), and \( \phi^h = [\phi^h_1, \ldots, \phi^h_M] \in \mathbb{R}_+^{1 \times M} \). The smallest allowed settings are \( \bar{\theta}_m, \bar{\phi}^v_{m}, \bar{\phi}^h_{m} \), while \( \underline{\theta}_m, \underline{\phi}^v_{m}, \underline{\phi}^h_{m} \) are the largest allowed settings.

The coverage metric \( \zeta \) and rate \( R \) are defined as in (6) and (7), respectively, where \( SINR^{DL}_{\cdot}(x) = [SINR^{DL}_1(x), \ldots, SINR^{DL}_N(x)] \in \mathbb{R}^{1 \times N} \) is a vector of all \( N \) users’ DL SINRs, and similarly for \( SINR^{UL}(x) \) for the UL SINR values. As \( R \) is the average sum-log-rate and already normalized by \( N \), the two metrics \( \zeta \) and \( R \) have numerical values with similar magnitudes. Therefore, no further normalization between them is necessary. The trade-off between outage probability and sum-log-rate can be adjusted by a rate weighting coefficient \( \beta \in [0, 1] \), denoted as \( \beta^{DL} \) in the downlink and \( \beta^{UL} \) in the uplink, enabling different coverage-capacity-trade-offs in each link. Similarly, the trade-off between DL and UL optimization is determined by an uplink weighting coefficient, denoted by \( \alpha \in [0, 1] \).

The optimization problem (8) is nonconvex due to the nonconcavity of utility function \( F_x \) [2], [32]. The joint optimization of rate and coverage is a challenging problem due to their conflicting nature, while a multicell environment creates coupling between each cell’s optimum settings: the optimal configuration of one cell’s antenna array depends on the settings of each neighboring cell due to inter-cell interference.

The formulated problem has three parameters to be configured for each cell, and hence there are a total of \( 3M \) optimization parameters each of which is continuous over the specified range. The search space considering all cells is exponential in \( M \), rendering an exhaustive search for the best settings impossible for moderate values of \( M \), even if the search space is discretized. It should be also noted that exhaustively exploring all possible settings in a trial-and-error manner can be a costly and time-consuming process. This approach incurs a significant computational cost, particularly when dealing with a large number of cells and parameters. Moreover, in real-life cellular networks, it can result in setting antenna parameters to configurations with no available performance data, leading to considerable performance degradation. Therefore, sample- and time-efficient methods that approach the unknowable optimum solution are highly desirable.

III. PROPOSED LEARNING FRAMEWORK

The aforementioned challenges of the site-specific antenna tuning problem motivate us to develop a novel data-driven and sample-efficient learning framework. We propose a methodology that leverages desirable features of (i) the ML-based black-box optimization technique Bayesian optimization (BO) and (ii) a metaheuristic search algorithm called differential evolution (DE). Together, this methodology allows us to approximately solve the nonconvex antenna optimization problem formulated in Section II-E quickly and efficiently, and in a scalable manner.

We are inspired to use BO since it is well-suited for solving such expensive-to-evaluate black-box optimizations with a limited computational budget [33], and it provides an accurate model that approximates the complex relationships between input parameters and the objective function. This surrogate model enables faster exploration by effectively eliminating unpromising candidates, ensuring that computational resources are allocated to the most promising ones. However, BO has some drawbacks that hinder its application in real-world environments. For example, it requires solving a nonconvex problem with increasing computational cost for deciding on each subsequent sampling point. This increase is cubic, making its cost prohibitive as the number of iterations (i.e., the training data size) grows [34]. This motivates the use of a different search algorithm to combine with the model building capability of BO.

For this, we opt for the evolutionary search framework, because of its strong search capabilities. For example, it can explore multiple areas of the search space simultaneously and can find solutions in high-dimensional search spaces [35]. Furthermore, it requires only constant time to generate new candidate solutions, which is far preferable to the cubic growth inherent to BO.

The hybrid algorithm capitalizes on the collaborative potential of the surrogate models and the evolutionary search process. The surrogate models guide the search towards promising regions, while the evolutionary search refines and improves the candidate solutions. Through iterative generations, the algorithm adaptively updates the surrogate models, enhancing their accuracy. This section details the steps of our proposed learning framework, whose flowchart is depicted in Fig. 2.

A. Generating New Candidates

The algorithm starts by randomly initializing a population matrix, \( X \in \mathbb{R}^{S \times 3M} \), with \( S \) individual vectors (i.e., antenna configurations) and calculating its real objective value, \( F_X \).

The \( i \)-th individual vector in \( X \) is

\[
 x_i = [\theta_1, \phi^v_1, \phi^h_1],
\]  

Fig. 2. The flowchart of the proposed algorithm, where \( X_0 \) is the randomly initialized population matrix at Step 0.
where \( \theta_i = [\theta_{i,1}, \ldots, \theta_{i,M}] \), \( \phi_{i} = [\phi_{i,1}^{U}, \ldots, \phi_{i,1}^{DL}, \ldots, \phi_{i,M}^{U}, \ldots, \phi_{i,M}^{DL}] \), and \( \phi_{i} = [\phi_{i,1}^{U}, \ldots, \phi_{i,M}^{U}, \ldots, \phi_{i,1}^{DL}, \ldots, \phi_{i,M}^{DL}] \) denote the \( i \)-th instance of the vectors \( \theta, \phi^{U}, \) and \( \phi^{DL} \), respectively, and \( X = [x_1^T, \ldots, x_S^T]^T, \) the next step is generating and evaluating new function values, which is performed by a modified DE framework. DE is a population-based evolutionary algorithm. As with other evolutionary algorithms, it reaches better solutions through mutation (11), crossover (12), and a selection strategy that keeps the member with the best objective function value. Hence, once the population is initialized with the matrix \( X \), a mutant vector is generated from each individual in \( X \) using one of the various kinds of DE mutation strategies which are denoted as DE/al/b, where \( a \) represents the vector to be mutated and \( b \) is the number of difference vectors used [36]. Among these strategies, we adopt DE/current-to-best/1 mutation scheme, which generates a mutant vector for the \( i \)-th individual as follows,

\[
v_i = x_i + F \cdot (x_{\text{best}} - x_i) + F \cdot (x_{r_1} - x_{r_2}),
\]

where the scale factor \( F \) is a positive real number that controls the population evolving rate and is usually less than 1. The vector \( x_{\text{best}} \) is the individual with the best objective function value in the current population, and \( x_{r_1} \) and \( x_{r_2} \) are the randomly chosen individuals. The motivation for choosing this mutation strategy is to reach a compromise between exploitation and exploration [37]. In the next step, a trial vector \( u_i = [u_{i,1}, \ldots, u_{i,3M}] \) is created for each mutant vector \( v_i = [v_{i,1}, \ldots, v_{i,3M}] \) by carrying out the crossover operator as

\[
u_{i,j} = \begin{cases}
    v_{i,j}, & \text{with probability } p_c \\
    x_{i,j}, & \text{otherwise}
\end{cases},
\]

where \( p_c \) is the crossover probability and determines the fraction of the trial vector that comes from the mutant vector [38]. Finally, in DE, a selection is made between each individual in the current population (\( x_i, \forall i \)), and the corresponding trial vector, \( u_i \), based on the calculated true objective function values, determining the population of the next iteration. The modification is made in this final step, where DE calculates the real objective function value of all individuals in the population at each iteration. Unfortunately, this step renders DE computationally expensive and time-consuming. However, in our proposed hybrid algorithm, this expensive step is replaced by the model building and prediction part of the BO with some custom modifications, as shown next in Section III-B. The computationally inexpensive surrogate model is thus substituted in place of time-consuming simulations or explorations.

### B. Model Generation and Prediction

The two major components of BO are a Bayesian statistical model (i.e., surrogate function) to model the objective function, and an acquisition function to decide on the next sample [39]. We employ only the first component in the proposed hybrid algorithm and choose a stochastic model Gaussian process (GP) as the surrogate function. We further differentiate from conventional BO by modeling UE SINRs independently with different input parameters, and hence have multiple GP models at each iteration. This enables us to have more accurate models and perform modeling in parallel, and thus accommodate a large number of UEs while preserving computational efficiency. Hence, after the trial population \( U = [u_{1}^T, \ldots, u_{S}^T]^T \) is created by (12), the uplink and downlink SINR models are generated by Gaussian process regression (GPR) for each UE using the current population \( X \). Then, for each individual vector in the trial population (\( u_i, \forall i \)), the uplink and downlink SINRs of each UE are predicted. GPR is an interpolation method ruled by prior covariances [33]. A GPR model \( g(x) \) is fully specified by its mean function \( \mu(x) \) and kernel function \( k(x, x') : g(x) \sim \mathcal{GP}(\mu(x), k(x, x')) \). To make predictions about unseen test cases, GPR utilizes the posterior. As the current population \( X \) is a matrix of training inputs and the trial population \( U \) is a matrix of test inputs, the conditional posterior for the test points is

\[
P(g_U|X, y, U) \sim \mathcal{N}(ar{g}_U, \text{cov } g_U),
\]

where

\[
\bar{g}_U = K(U, X)[K(X, X) + \sigma_n^2 I]^{-1}y,
\]

\[
\text{cov } g_U = K(U, U) - K(U, X)[K(X, X) + \sigma_n^2 I]^{-1}K(X, U),
\]

\[
g_U = [g(u_1), \ldots, g(u_S)], \quad y = [\text{SINR}_{DL}(X), \text{SINR}_{UL}(X)],
\]

and \( \sigma_n^2 \) is an independent noise variance. SINR\(_{DL}\) and SINR\(_{UL}\) are the downlink and uplink UE SINR values, respectively, corresponding to each antenna configuration in \( X \), and \( K(\cdot, \cdot) \) denotes the covariance matrix. For a more detailed explanation of GPs, please see [40].

#### C. Selection

After UE SINR values, \( \hat{\text{SINR}}_{DL}(U) \) and \( \hat{\text{SINR}}_{UL}(U) \), are predicted with the GPR model, the objective function value of the trial population, \( F_U \), is calculated using these predictions. The individual with the best estimated objective function value is then chosen among the trial population, and only that individual’s real objective function value, \( F_{\text{true}} \), is obtained from the simulator. If this value is better than the worst objective function value in the current population, \( F_{\text{worst}} = \min(F_X) \), the new candidate solution, \( u_{\text{best}} \), is substituted for that worst individual, \( x_{\text{worst}} \). The training dataset is thus updated. In each iteration, we have a population \( X \) with \( S \) individual solutions, including at most one new solution. This holds the computational cost of GP modeling constant by keeping the training data size fixed. As this process is repeated, the current population progresses together to a better region, and when the termination criterion is satisfied, the best individual in the current population, \( x_{\text{best}} \), is chosen as the desired solution.

#### D. Neighborhood Approach

A caveat of using GP is that it restricts the dimension of the problem, and is best suited for optimization over continuous domains with about twenty or fewer decision variables.
(i.e., input parameters) [39]. It has also been investigated for medium-scale problems with 20-50 decision variables, concluding that it can still be an effective approach in that range [41]. However, it is not suitable for higher dimensional problems. In the defined problem, (8), we have 3M input parameters, corresponding to M downtilt angles, M vertical HPBWs, and M horizontal HPBWs, where M is the number of total cells in the network. Hence, this dimensionality constraint restricts the network size. To relax this restriction, we define a neighborhood for each UE, which includes the cells with a large measured RSRP. Considering that cells with low RSRP do not have a significant effect on the UE SINR, this neighborhood approach holds the dimension of the problem fixed and renders it independent of M. Thus, it helps GP have an accurate and computationally feasible model which can be successfully scaled to much larger networks.

The neighborhoods are defined once at the beginning of the proposed algorithm by initializing the parameters of all cells to the specific values – $\theta_1^c, \phi_1^c, \phi_h^c$ – and neighboring cells are then chosen based on the calculated uplink and downlink RSRP values. Specifically, for a $N$-sized neighborhood, $\mathcal{N}$ cells with the highest RSRP values are selected for each UE. By using the same neighborhoods throughout the simulation, it is assumed that there is no significant change in the neighborhood of UEs while the antenna parameter settings change during the optimization. This assumption is made to maintain the accuracy of the generated models, and we validated it in our simulations by ensuring that for each UE, the majority of its strongest interferers are captured in its neighborhood with high probability. It should be noted that alternative methods are available for defining neighborhoods, such as leveraging insights from context information, and our framework offers flexibility in modifying the neighborhood definition.

Overall, our proposed sample-efficient learning algorithm, whose steps are summarized in Algorithm 1, begins by defining a neighborhood for each UE. Then, it follows the steps explained in Section III-A to III-C. Notice that with the involvement of the neighborhood approach, the input vector of the $n$-th UE’s GPR model consists of only the parameters of its neighboring cells. Hence, each UE has a different input parameter population to define a model for its SINR.

We evaluate the proposed learning framework for the defined problem using three metrics.

1) **Average sum-log-rate**, $R$, is defined in (7). It is a throughput metric used in the objective function, and as a performance metric, it measures the throughput improvement of the proposed algorithm compared to the 3GPP default settings and other comparative algorithms.

2) **Outage probability** is defined in (6). This metric measures the coverage improvement that the proposed algorithm achieves compared to the 3GPP default settings and other comparative methods.

3) **UE SINR** values are derived from WiNGS after optimizing the antenna parameters of the cells, and their empirical CDF plots are compared with the 3GPP default settings and other comparative algorithms. In addition to measuring the UE SINR improvement, this metric provides insights into the fairness of the algorithm by identifying the improved SINR regions.

Algorithm 1 Sample-Efficient Learning Algorithm

```plaintext
Input: $X = [x_1^T, \ldots, x_M^T]^T$, SINR$(X)$, $F_X$
1: for $\text{iter} = 1, 2, \ldots, N_{\text{iter}}$ do
2: $v_i = x_i + F \cdot (x_{\text{best}} - x_i) + F \cdot (x_{r_1} - x_{r_2}), \forall i$
3: $u_{i,j} = \begin{cases} v_{i,j}, & \text{with probability } p_c, \\ x_{i,j}, & \text{otherwise} \end{cases}$
4: $u_i = [u_{i,1}, \ldots, u_{i,3M}], U = [u_1^T, \ldots, u_M^T]^T$
5: Construct GP models for UL and DL SINR of $n$-th UE using the antenna parameters of its neighboring cells.
6: Predict SINR$_{UL}$($U$) and SINR$_{DL}$($U$) with the created GP models.
7: end for
8: $F_{\text{UL}} = (1 - \alpha) f(\text{SINR}_\text{UL}(X)) + \alpha f(\text{SINR}_\text{DL}(X))$
9: $u_{\text{best}} = \arg \max_u F_{\text{UL}}$
10: Observe $F_{\text{upbest}}$
11: if $F_{\text{upbest}} \geq F_{\text{down}} = \min(F_X)$ then
12: $x_{\text{worst}} \leftarrow u_{\text{best}}$
13: end if
14: end for
Output: $x_{\text{best}} = \arg \max_x F_X$
```

IV. Simulation Details

We perform our experiments on a state-of-the-art 5G NR simulator, WiNGS, developed by AT&T Labs. WiNGS is used within AT&T for developing and evaluating advanced air interface and radio access network features across a range of realistic deployment scenarios based on both statistical modeling tools and real-world network data input. This event-driven, modular, fully dynamic system level simulator (SLS) closely models the air interface functionality and operations – including PHY, MAC, RLC, PDCP, SDAP, and RRC layers – of the 5G NR radio access network protocol stack. The wireless channels for the access links are generated using 3GPP-defined statistical models with both long-term line-of-sight and non-line-of-sight path loss, shadowing, and short-term fading effects. BS deployments can be modeled based on a fixed grid or random heterogeneous layouts and even based on real-world deployment data, including modeling antenna array geometry on a per-site basis.

As a dynamic SLS, WiNGS generates a variety of per-user metrics including RSRP, L1 channel state information, and SINR measurements by taking into account inter-cell interference, which are used in the link adaptation and resource allocation blocks for modulation coding scheme and transport block size selection every scheduling interval. In addition, practical digital and analog codebooks are used to support cell-specific and user-specific beamforming.

On this high-fidelity simulator, we consider two outdoor HetNet deployments to experimentally verify the proposed...
framework and show its scalability to large network sizes. Layout 1 is a hexagonal heterogeneous layout with a total of $M = 32$ cells (7 macrocells with three sector antennas and 11 small cells) and $N = 62$ UEs which are uniformly distributed to different locations. Layout 2 is based on real-world deployment data, and it comprises 200 uniformly distributed UEs and a total of $M = 77$ cells (19 macrocells with three sector antennas and 20 uniformly distributed small cells). The macrocells have a height of 25m, small cells of 10m, and UEs of 1.5m. The distributions of macrocells, small cells, and UEs in the two HetNet deployments are shown in Fig. 3.

We compare our proposed algorithm with five different baselines in two different simulation environments. Three of these baselines – 3GPP default settings, random search, and conventional BO with expected improvement – are implemented in the described simulation environment (i.e., WiNGS), and the results for the other two – the deep deterministic policy gradient algorithm (DDPG) and BO with q-expected hyper-volume improvement [42] – are obtained from the work [19] in which a MATLAB tool suite called QuaDRiGa [43] is used. Regarding the implemented three baselines, in the 3GPP default settings, a single configuration (e.g., $\theta = 12^\circ$, $\phi_v = 10^\circ$, and $\phi_h = 70^\circ$) that is the same for all cells is chosen through an extensive search, as in 3GPP [3], [25]. Random search draws random samples from the search space and keeps the best configuration at each iteration during optimization. BO and the proposed algorithm use the same kernel function and hyperparameter initialization, and a population with the same number of individuals is randomly initialized at the beginning of random search, BO, and the proposed algorithm.

The simulations start by initializing the tilt, vertical HPBW, and horizontal HPBW of each cell’s antenna array to $\theta = 12^\circ$, $\phi_v = 10^\circ$ and $\phi_h = 70^\circ$, respectively. A neighborhood for each UE is then determined by choosing $N = 8$ and 10 neighboring cells whose RSRP values are maximum in Layout 1 and 2, respectively. Throughout the simulation, the parameters of these neighboring cells are used for modeling the SINR of the associated UE. After a neighborhood for each UE is determined, initialization is performed by randomly choosing $S = 200$ antenna configurations for each cell.

In all subsequent simulations, the Matérn $5/2$ ARD kernel function is used for GP. It is one of the most common kernel classes used in GP and a popular choice in BO due to its flexibility in smoothness. The Matérn covariance between two data points, $x_i$ and $x_j$ is

$$k(x_i, x_j) = \frac{2^{1-\nu}}{\Gamma(\nu)} \left(\frac{\sqrt{2\nu}}{l}d(x_i, x_j)\right)^\nu K_{\nu}\left(\frac{\sqrt{2\nu}}{l}d(x_i, x_j)\right),$$

(16)

where $K_{\nu}$ is a modified Bessel function, and $\nu$ and $l$ are the positive hyperparameters of the kernel function. The value $\nu$ controls the smoothness of the function while $l$ is a length scale parameter. The optimization of these parameters follows a maximum likelihood estimation method [40], and the gpml package [44] is used in the implementation of GP.

Control parameters of DE – crossover probability $p_c$ and scale factor $F$ – are experimentally chosen as 0.8 and 0.7, respectively. In the literature, a reasonable value for $F$ is usually between 0.4 and 1 and $p_c$ is between 0.3 to 0.9, where the higher values of $p_c$ speed up convergence [38]. Overall, these values depend on the objective function and the problem. The key simulation parameters are summarized in Table I.

V. RESULTS AND DISCUSSION

The proposed algorithm is evaluated in various environments described in Section IV considering downlink-only (i.e., $\alpha = 0$), uplink-only (i.e., $\alpha = 1$), and joint
uplink-downlink directions of a cellular system. Results comparing the algorithm performance with baseline algorithms are presented in Fig. 4 - 6 for Layouts 1 and 2, with a focus on downlink-only optimization and downlink performance metrics. Although BO is used as one of the comparison algorithms in Layout 1, it is not implemented in Layout 2, where the dimension of the input parameters (i.e., antenna parameters) is 231 (77 cells with 3 parameters), because conventional BO is not deemed suitable for tackling problems of this magnitude.

The performance of the uplink and downlink joint optimization compared to the downlink-only and uplink-only optimization are then presented in Fig. 10 and 11 for Layout 1. The results are obtained by implementing and evaluating the proposed algorithm and the comparative baselines on WiNGS. They are calculated over 5 realizations of each layout and plotted with the results using 3GPP default settings, where natural logarithm is used in the average sum-log-rate plots.

Finally, the comparison results of our proposed algorithm with DDPG and BO with q-expected hypervolume improvement are presented in Fig. 12.

A. Performance Comparisons with Baseline Algorithms

In this section, we compare the numerical results of our approach with other baseline algorithms where the values $\alpha$, $\beta_{DL}$, and $T$ in the problem (8) are set as 0, 0.5, and 0 dB, respectively.

1) Throughput and Coverage Gain Are Large Compared to Baselines: Fig. 4 and 5 highlight the improvement achieved by the proposed algorithm in terms of both sum-log-rate and outage probability. It can be observed from Fig. 4a that the proposed algorithm reaches the peak value around 400 iterations and then converges while BO converges to a sub-optimal point around that iteration. Meanwhile, random search increases slowly and its value remains far below the proposed algorithm even at the 800-th iteration. Similar observations can be made for Fig. 4b. All of the algorithms optimize the sum-log-rate and outage compared to the 3GPP default settings. However, by increasing log-utility by over 4 times and decreasing outage probability by around 90%, the proposed algorithm outperforms conventional BO and random search, which achieve around 2 times more log-utility and decrease outage probability by around 50% and 44%, respectively, compared to the 3GPP default settings.

| TABLE I SIMULATION PARAMETERS |
|--------------------------------|
| **Optimization Parameters**   | **Values** |
| Crossover probability, $p_c$  | 0.8        |
| Scale factor, $F$             | 0.7        |
| Population size, $S$          | 200        |
| Neighborhood size, $N$        |             |
| Threshold, $T$                | 0 dB, 10% SINR |
| Total iteration number, $N_{it}$ | 1000       |
| Sum-log-rate and outage       |             |
| probability trade-off, $\beta$| $[0.2, 0.5, 0.8, 1]$ |
| UL weight (vs. DL), $\alpha$  | $[0.2, 0.5, 0.8]$ |
| $\theta^*, \phi^*$           | $\{0^\circ, 0^\circ, 5^\circ\}$ |
| $\{\theta^*, \phi^*\}$       | $\{25^\circ, 65^\circ, 100^\circ\}$ |
| $\{\theta^*_{DL}, \phi^*_{DL}\}$ | $\{12^\circ, 10^\circ, 70^\circ\}_{DL}$ |

| **System Parameters**         | **Values** |
| Carrier frequency             | 2 GHz      |
| Bandwidth                     | 10 MHz     |
| Subcarrier spacing            | 15 kHz     |
| Number of users, $N$          |             |
| Number of cells, $M$          |             |
| Macrocell transmit power      | 43 dBm     |
| Small cell transmit power     | 30 dBm     |
| Maximum uplink transmit power | 23 dBm     |
| Macrocell antenna height      | 25 m       |
| Small cell antenna height     | 10 m       |
| User height                   | 1.5 m      |
2) Algorithm Makes a Trade-Off Between Sum-Rate Maximization and Fairness: The right shift in empirical CDFs of the UE SINR, Fig. 6, shows that the optimal angle values found by the algorithm provide a better overall SINR distribution for UEs than the 3GPP and other comparative baselines. The effect of utilizing the sum-log-rate can be noticed from this figure that the performance improvement is not limited to a specific group of users; instead, there is an improvement across the whole range of performance metrics. This implies that the throughput and coverage gains shown in Fig. 4 and 5 are achieved by making UEs in all SINR ranges better off, highlighting the fairness aspect of the algorithm.

Table II depicts the downlink UE SINR improvement that the proposed algorithm delivers in both layouts. We can observe that in Layout 1, the proposed framework has around 5.95 dB, 2.16 dB, and 1.55 dB SINR improvement for the UEs in the outage range (10% SINR), and 7.12 dB, 3.78 dB, and 2.90 dB increase for the median UE SINR compared to the 3GPP default settings, random search, and conventional BO, respectively. In Layout 2, these improvements are around 3.50 dB and 2.57 dB for the outage SINR; and 6.15 dB, and 3.69 dB for the median SINR compared to the 3GPP default settings and random search, respectively. The performance of the BO being close to random search in Layout 1 supports our claim that it is not a suitable algorithm for optimization problems with high input dimensions, as 96 input parameters are optimized in this layout. The degradation of the BO performance with increasing dimensionality can also be observed in Fig. 7.

3) Algorithm Gracefully Scales to Large Network Sizes: The performance results for Layout 2, consisting of 19 macrocells with three sector antennas and 20 small cells (Fig. 5 and 6b), demonstrate the successful scalability of our algorithm to larger network sizes, while consistently outperforming random search and the 3GPP default settings. To assess the performance of our proposed algorithm in
Fig. 7. Comparison of the proposed algorithm (PA) and Bayesian optimization (BO) in terms of downlink UE SINR in Layout 1. A fraction of cells (i.e., 1, 8, and 16 cells) among $M = 32$ are optimized.

Table II

| Algorithm               | 10% Outage SINR (dB) | Median SINR (dB) |
|-------------------------|----------------------|------------------|
| Proposed algorithm      | 1.700                | 9.635            |
| Bayesian optimization   | 0.1517               | 6.737            |
| Random search           | -0.4635              | 5.860            |
| 3GPP default settings   | -4.250               | 2.517            |

a) Layout 1

Fig. 8 shows the histogram of optimal parameters found by the proposed algorithm over 5 realizations of Layout 2. Fig. 8a and 8b present the macrocell and small cell parameters, respectively. Only cells that are associated with a UE are included in these histograms. For cells not associated with any UE, we observe that most of them avoid interfering with other cells by choosing small vertical and/or horizontal HPBWs. For the other cells, we can observe from the histograms that antenna parameters of both macrocells and small cells mainly concentrate on the higher values. This tendency is related to the fact that we have a dense network with a large number of UEs. So, most of the cells are serving multiple UEs, and they are trying to cover all of their users by creating large beams. For example, the cell located around (735, 352) with azimuth $240^\circ$ sets its vertical HPBW to $59.5^\circ$ and its horizontal HPBW to $99.7^\circ$. The width of the beam becomes narrower for the cells with less number of UEs. They take advantage of focusing the energy on the served users and having a narrower beam, avoiding interference with neighboring cells. For example, the cell located around (735, 352) with azimuth $0^\circ$ sets its vertical HPBW to $8.82^\circ$ and its horizontal HPBW to $11.0^\circ$.

Besides the number of associated UEs and antenna azimuth, BS height also affects the antenna beam pattern. For example, since the height of the small cells is smaller and closer to the optimized in the defined problem), the proposed algorithm exhibits a rightward shift in the UE SINR distribution compared to BO, indicating evident improvement. This performance difference becomes even more pronounced when optimizing all 32 cells in the network, as demonstrated in Fig. 6a earlier.

We can thus infer from the figures that our proposed algorithm consistently enhances UE SINR as the number of optimized cells increases, while conventional BO struggles to keep up, showing that our proposed algorithm has better scalability to large networks.

The figures reveal that the results of BO and our proposed algorithm closely align when only 1 cell is optimized. Similarly, for the case of 8 optimized cells, BO and our algorithm exhibit comparable performance. However, as the number of optimized cells increases, our proposed algorithm starts to outperform BO noticeably. For instance, in the scenario with 16 optimized cells (i.e., a total of 48 input parameters are relation to conventional BO as the network size increases, we also conducted experiments with varying numbers of cells (i.e., input parameters). Fig. 7 presents the results of this comparison for Layout 1, focusing on scenarios where 1, 8, and 16 cells out of a total of 32 are optimized. In order to present the results clearly, Fig. 7a displays the CDF for the scenarios where 1 cell and 8 cells are optimized, while the CDF for the case where 16 cells are optimized are separated from them and presented in Fig. 7b.

The figures reveal that BO and our proposed algorithm closely align when only 1 cell is optimized. Similarly, for the case of 8 optimized cells, BO and our algorithm exhibit comparable performance. However, as the number of optimized cells increases, our proposed algorithm starts to outperform BO noticeably. For instance, in the scenario with 16 optimized cells (i.e., a total of 48 input parameters are
height of the UE, it is expected that they have smaller downtilt values and larger HPBW on the vertical plane compared to macrocells in order to serve more UEs.

B. Trade-Off Between Capacity and Coverage

To observe how two objectives (i.e., coverage and capacity) compare, we experiment with the $\beta^{DL}$ coefficient after setting $\alpha = 0$. Fig. 9 shows the empirical CDF of UE SINR for $\beta^{DL}$ values of 0.2, 0.5, 0.8, and 1. In this experiment, we use $\beta^{DL} = 1$ plot to determine the 10% SINR and set the $T$ threshold to this value in order to better observe the effect of smaller $\beta^{DL}$ on the outage optimization (i.e., lower SINR values). In the case of $\beta^{DL} = 1$, we are trying to optimize the sum-log-rate of users without considering how many users are in the outage. Hence, the algorithm can sacrifice some users to increase the overall sum-log-rate. When $\beta^{DL}$ is set to small values such as 0.2, the optimization problem is mostly solved for the outage. Thus, the main objective of the algorithm is to make outage probability as close to 0 as possible, and it is nearly indifferent to SINR increase if it is already higher than the threshold. Fig. 9 confirms this as the $\beta^{DL} = 0.2$ plot is the leftmost while its outage probability is the lowest compared to the other $\beta^{DL}$ values. On the other hand, $\beta^{DL} = 1$ results in the best SINR performance while its outage probability is the highest. For the other $\beta^{DL}$ values, UE SINR CDF plot is in-between $\beta^{DL} = 0.2$ and 1. We can conclude from the figure that for the given layout, $\beta^{DL} = 0.8$ makes an effective trade-off between sum-log-rate and outage probability as its CDF curve is very close to the curve with $\beta^{DL} = 1$, and also it has an outage probability that is close to the one with $\beta^{DL} = 0.2$.

C. Uplink and Downlink Joint Optimization Performance

There are significant differences in transmit power and interference characteristics between UL and DL, as previously discussed. In the DL, interference is often the primary limiting factor, rather than received signal strength, due to the use of a large number of antennas and high transmit power by...
Fig. 10. Empirical CDF plot of UE SINR values after optimization for DL-only, UL-only, and UL-DL joint in Layout 1 for $\alpha = 0.5$.

Fig. 11. Empirical CDF plot of UE SINR values after optimization for DL-only, UL-only, and UL-DL joint in Layout 1 for different UL weightings $\alpha$.

BSs. However, in the UL, UEs have fewer antennas and less transmit power, which can limit the ability of the UL signal to be received at the BS. Therefore, the BS array geometry has a significant impact on the UL SINR. Additionally, interference sources differ between the two links, with UL interference being generated by mobile UEs while DL interference is dictated by the fixed locations of BSs. As a result, optimal antenna configurations for the two links differ due to these inherent asymmetries.

To investigate this difference, we begin by performing downlink-only and uplink-only optimizations. This allows us to observe whether there are substantial and frequent differences in the optimal angle and beamwidth values on a cell-by-cell basis between the two cases. Subsequently, we perform an uplink-downlink joint optimization to find the best values per cell and the loss from the optimal DL or UL values.

Fig. 10 and 11 illustrate the resulting distribution of UE SINR after optimization for three scenarios: uplink-only optimization (UL-only), downlink-only optimization (DL-only), and joint uplink-downlink optimization (UL-DL joint). The uplink weight $\alpha$ is set to 0.5 in the joint optimization shown in Fig. 10 while its value varies in Fig. 11. In both cases, the outage threshold, $T$ is set as 0 dB, and the trade-off coefficients between rate and outage probability, $\beta_{UL}$ and $\beta_{DL}$, are chosen as 0.2 and 0.8, respectively. These $\beta$ values are chosen to focus the optimization more on data rates in downlink and coverage in uplink transmission considering the limited UE transmit power. To better track these desired improvements, we utilize a log scale for uplink UE SINR and a linear scale for downlink UE SINR. The linear scale effectively captures improvements across all SINR regions in the DL SINR plot, while the log scale allows us to focus specifically on improvements in the low-SINR region in the UL SINR plot.
1) Throughput and Coverage Gain is Large Compared to Single Direction Optimization: Fig. 10 clearly shows a significant performance loss when using single direction optimization. UL-only optimization degrades downlink UE SINR performance, while DL-only optimization degrades uplink performance. This occurs because DL-only (UL-only) optimization only considers the performance of the downlink (uplink) direction to set the antenna parameters, disregarding the uplink (downlink) performance. Joint optimization, however, increases both median and 10% outage SINR of uplink and downlink compared to the DL-only and UL-only optimization, respectively. Specifically, the quantitative results show that compared to DL-only optimization, there is an increase of approximately 4.28 dB and 5.82 dB in the uplink median and 10% outage SINR, respectively, while the downlink median and 10% outage SINR increases by around 4.38 dB and 3.47 dB, respectively, compared to UL-only optimization. The chosen values of $\beta_{UL}$ and $\beta_{DL}$ are highlighted by two observations: first, the improvement in uplink 10% outage SINR is better than the improvement in uplink median SINR; and second, the improvement in downlink median SINR is better than the improvement in downlink 10% outage SINR. The numerical results and figures suggest that UL-DL joint optimization with the selected $\beta$ values significantly improves uplink coverage compared to DL-only and downlink data rate compared to UL-only optimization, as desired.

D. Trade-Off Between Uplink and Downlink Optimization

We experiment with $\alpha$ values in optimization problem (8) to understand how the optimal parameter values and the loss differ compared to the case where $\alpha = 0.5$ (Fig. 10). The comparison plots, which include the results of both the single and joint direction optimization, are presented in Fig. 11 for different $\alpha$ values. Fig. 11a depicts the distribution of downlink UE SINR while Fig. 11b shows the uplink UE SINR distribution. In both cases, we can observe that aligning with the objective, UL-DL joint optimization curve approaches to UL optimization curve as $\alpha$ increases, which means that joint optimization mainly optimizes uplink transmission. On the other hand, it approaches the DL optimization curve as $\alpha$ decreases. Hence, by optimizing the $\alpha$ value according to the needs of the different networks, one can find a good compromise between uplink and downlink transmission, which will make the performance of the overall transmission better. We can infer from the figure that for the given layout, $\alpha = 0.5$ provides a good balance between uplink and downlink, which effectively optimizes for downlink capacity and uplink coverage. However, note that UL-DL joint optimization performs significantly better than the UL-only (DL-only) optimization even with $\alpha = 0.8$ ($\alpha = 0.2$), achieving better overall downlink (uplink) UE SINR.

Establishing trade-off coefficients $\alpha$ and $\beta$ in real networks involves conducting network-specific analysis by considering network requirements and user demands. For instance, in urban macro scenarios, prioritizing downlink capacity while ensuring adequate uplink coverage for reliable UL control channels is often required. On the other hand, situations involving user-generated content and real-time interactions may necessitate a focus on prioritizing uplink capacity. Fine-tuning these coefficients as hyperparameters during optimization allows for customization based on network-specific needs.

E. Complexity and Efficiency Analysis

We perform a further analysis of our algorithm by comparing it with an RL method – DDPG – and BO. In contrast to our earlier comparison with BO, this evaluation is based on the problem formulation and simulation environment presented in [19], which is accessible at [45], and employs q-expected hypervolume improvement as the acquisition function. This formulation optimizes downtilt angle and transmit power, aiming to address both under-coverage (i.e., areas lacking sufficient received signal strength) and over-coverage (i.e., locations with excessive interference from neighboring cells). The downtilt angle can take discrete values in the range of $[0, 10]^\circ$, while transmit power has continuous values within $[30, 50]$ dB. For more details about the simulation environment and the problem formulation, please refer to [19]. In this paper, we leverage these comparisons to demonstrate the sample efficiency and time efficiency of our algorithm compared to RL and BO, respectively.

Fig. 12a shows the BO and DDPG frontiers which are plotted using the results in [19]. These results are obtained by using 1012 evaluations (512 for initialization and 500 for optimization) for BO and 600,000 evaluations for DDPG. Initially, we analyzed our proposed algorithm using the same number of evaluations with BO, for both initialization and optimization, observing that it achieves a slightly better frontier compared to BO and closely matches the performance of RL. Subsequently, we aimed to enhance the time and sample efficiency for the proposed algorithm and reduce the number of initialization evaluations. Fig. 12a depicts the performance of our algorithm after 750 evaluations (200 for initialization and 550 for optimization) alongside random search, BO, and DDPG. Remarkably, we observe that even 750 evaluations are sufficient to closely align with the performance of DDPG. These results demonstrate that both BO and our approach improve sample efficiency by over two orders of magnitude relative to DDPG, and our approach can achieve the performance of DDPG with this significant difference in the number of evaluations.

Decreasing the number of initialization evaluations to 200 makes a notable difference and helps increase time efficiency further compared to BO since as it is mentioned earlier, the GPR method, which is used in both our proposed approach and BO, has cubic computational complexity, $O(T^3)$, where $T$ is the number of training data samples. Hence, when we use 200 evaluations for initialization, it means that $T = 200$ in our proposed algorithm throughout the optimization evaluations while $T$ starts from 200 and keeps increasing with each iteration in BO. This implies that at every iteration, the computational time of BO is increasing, which is another dimensional restriction that BO has. This phenomenon can be clearly observed from Fig. 12b which depicts the cumulative elapsed time for model building and finding a new candidate
Fig. 12. Comparison of the proposed algorithm, BO, and DDPG in terms of sample and time efficiency.

at each iteration for both BO and our proposed algorithm. In each method, 200 evaluations are used for initialization, and the expected improvement acquisition function is used for BO. We show that the cumulative elapsed time of BO can be well approximated by a cubic function (i.e., $ax^b + c$, where $a = 4.3 \cdot 10^{-6}$, $b = 3.01$ and $c = 4223$), shown as a dashed line in Fig. 12b while our proposed algorithm demonstrated to have linear time complexity (i.e., $ax^b + c$, where $a = 1.71$, $b = 1.01$ and $c = 2067$). We can also infer that starting the algorithms with 512 evaluations instead of 200 increases the time elapsed at each iteration, thus shifting both curves up. This emphasizes the significance of achieving optimal performance with a minimal number of evaluations.

It is worth noting that the results presented in Fig. 12 correspond to a low dimensional problem, consisting of only 5 BSs with three sector antennas and 30 input parameters to optimize. Additionally, due to the problem definition of the reference [19], we were restricted to create models for the coverage and capacity metrics instead of individual UE SINRs, resulting in similar modeling with BO. Consequently, it is expected that there would not be significant performance differences between the algorithms in this case. However, it should be emphasized that our proposed algorithm demonstrated a clear advantage in small-scale networks in terms of sample and time efficiency compared to DDPG and BO, respectively, which was the primary focus of this subsection.

Furthermore, previous sections have already demonstrated the successful scalability of our proposed algorithm to larger networks. As depicted in Fig. 7, in scenarios with a larger number of input parameters, the performance difference between our algorithm and conventional BO in terms of UE SINR becomes more pronounced. Our proposed algorithm consistently improves UE SINR as the number of optimized cells increases, while conventional BO cannot keep up. This highlights the better scalability of our proposed algorithm to large networks, and these large network optimizations are thus the ones we expect to yield more significant performance gains compared to other approaches.

VI. CONCLUSION AND FUTURE WORK

In this paper, we study the uplink and downlink joint capacity and coverage optimization (CCO) by tuning parameters – downtilt angle, vertical half-power beamwidth (HPBW), and horizontal HPBW – of each cell’s antenna array. We provide a data-driven framework that is suitable for real-world implementation for this nonconvex and challenging problem. Considering the importance of sample and time efficiency in real-world antenna optimization, we show that our proposed algorithm is significantly sample-efficient compared to the RL approach (i.e., deep deterministic policy gradient), and time-efficient compared to conventional Bayesian optimization (BO). Using the state-of-the-art system-level simulator developed by AT&T Labs and the layout with 19 macrocells (whose locations are based on real-world deployment) and 20 small cells, we also show that our algorithm successfully scales to large network sizes while preserving its gain compared to comparative baselines – 3GPP default settings, random search, and conventional BO. Moreover, numerical results from the experiments on the simulator indicate that the downlink rate and uplink coverage can be greatly improved by performing joint optimization compared to the single direction optimization. Overall, this paper demonstrates that CCO problems that only optimize the downlink have poor uplink performance, and there are significant gains to be harvested from site-specific data-driven antenna parameter optimization which can be achieved in a fast, scalable, and automated fashion.
Future work could analyze the robustness of the proposed method over time to different UE locations and mobility, and it could include load-aware user associations. Extensions to higher carrier frequencies, larger antenna arrays, and other transmission modes would also be of interest. Moreover, our proposed algorithm can be combined with more advanced initialization approaches to further increase sample efficiency by reducing its convergence time. Additionally, alternative approaches for defining neighborhoods can be explored to increase the accuracy of the optimization by improving the validity of the generated models. Finally, given that we have provided a practically applicable learning framework in this paper, an important extension is to consider how to take this framework into a real cellular system (e.g., when and how often to train the algorithm and change parameter settings).

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