Abstract—With the advent of millimeter wave (mmWave) communications, the combination of a detailed 5G network simulator with an accurate antenna radiation model is required to analyze the realistic performance of complex cellular scenarios. However, due to the complexity of both electromagnetic and network models, the design and optimization of antenna arrays is generally infeasible due to the required computational resources and simulation time. In this paper, we propose a Machine Learning framework that enables a simulation-based optimization of the antenna design. We show how learning methods are able to emulate a complex simulator with a modest dataset obtained from it, enabling a global numerical optimization over a vast multi-dimensional parameter space in a reasonable amount of time. Overall, our results show that the proposed methodology can be successfully applied to the optimization of thinned antenna arrays.

Index Terms—5G, machine learning, optimization, antenna design, emulation.

I. INTRODUCTION

Massive Uniform Planar Arrays (UPAs) operating in the mmWave frequency range will be adopted in the 5th generation of mobile networks (5G) as the key enablers to meet the challenging requirements of the new standard. Large antenna arrays can compensate for the propagation and penetration losses at such high frequencies thanks to beamforming techniques, synthesizing 3D beams that can focus the transmitted power towards specific users [1], increasing the antenna gain and thus increasing the received power. Furthermore, beamforming can help exploit the unique propagation characteristics of the mmWave channel, such as spatial sparsity, to reduce the interference among users.

These ambitious goals require a novel approach to antenna design and optimization. Antenna arrays can no longer be designed and optimized without considering the network topology: in addition to the common antenna design goals, such as decreasing the side-lobe level or maximizing the directivity, more global, network-oriented requirements need to be taken into account. Such requirements dramatically increase the complexity of the optimization problem, as it moves from the bare electromagnetic to the network domain. As both antenna prototyping and network deployment tests are prohibitively expensive for both academia and most industry, electromagnetic and network simulators are often employed. In [2], the accurate modeling of antennas in network simulators was proved to be decisive, further confirming that design and optimization need to carried out jointly.

Heuristic simulation-based optimization is generally not feasible, as such detailed simulators are both time and computationally expensive. Indeed, the large number of iterations needed by optimization algorithms prevents the use of simulations requiring hours (or even days) of running time. For this reason, in this paper, we propose and evaluate a Machine Learning (ML) framework that can mimic a given simulator and allows us to achieve any network optimization objective in a reasonable amount of time. The general framework is represented in Fig. 1 and has been recently described in detail elsewhere [3]. The diagram shows how the parameter optimization can be achieved through the ML-based emulator, which only requires a single training phase done using a dataset of simulated data.

In this work, differently from [3], the focus is on the optimization of thinned arrays. This manuscript is organized as follows: in Section II the new design challenge is described; in Section III new learning techniques are tested for the emulation task, to tackle the increased complexity of the problem; finally, in Section IV we present the results of the optimization, while Section V concludes this work and describes some remaining open challenges.

A. Related Works

Recently, ML techniques have started to be applied as a tool to solve many kinds of problems. Also in the communication field, there exist many works adopting learning-oriented approaches to address complex transmission issues. Particular
attention has been gathered by the new database proposed in [4], as it lays the premises for a common research ground.

One common application of ML is parameter estimation, where great results were achieved even where the most sophisticated classical techniques failed. An example can be found in [5], where the authors try to estimate the downlink channel starting from samples of the uplink channel. While well-known signal processing techniques (e.g., the Wiener filter) were not able to perform a good estimate, the ML approach proposed by the authors yielded very good results.

ML has been successfully applied also at the network layer. Innovative ideas and proposals have challenged even the most resilient classical paradigms such as the ISO/OSI architecture [6]. These new approaches started showing their potential in the increasingly heterogeneous network scenarios, e.g., when facing the high data load and quality of experience required for video streaming [7].

Moreover, the authors in [8] use Deep Neural Networks (NNs) to optimize the allocation algorithm in a wireless resource management problem. The proposed concept is similar to the one described in our work, as a learning tool is used to approximate a complex input-output function. However, the authors also include the optimization step into the learning process and use many more training samples to accommodate the needs of their deep architecture.

Considering that at high frequencies, such as in the mmWave bands, strong attenuations are present, quantifying the actual antenna gain obtained due to the radiation pattern is fundamental to precisely evaluate any mmWave system. For this reason, we have used previous works [2], [3] as the main references for both the network and the antenna characterizations.

Finally, regarding the specific problem of thinned arrays, several works exist on their optimization at the antenna level. A reference for the general theory and results can be found in [9]. On the optimization side, [10] and [11] apply genetic algorithms to the activation mask of the array to further optimize the performance. In Section II-A we list the parameters to be optimized.

Fig. 2. Example of a generated array. Dashed lines separate the four quadrants, while black and gray dots represent respectively the activated antennas and the array lattice. The top-left quadrant is generated and then mirrored to the other three.

Urban Micro-cell (UMi) scenario with no Outdoor-to-Indoor (O2I) losses.

The goal of this study is to understand whether irregular thinning is a desirable property in an array. In Section II-A we describe the adopted irregular thinning approach, while in Section II-B we list the parameters to be optimized.

### A. Antenna Array Generation

To simplify both the implementation and the optimization, thinning is defined by means of an activation mask over a regular lattice of dummy antennas. Namely, a large antenna array lattice is created but only some of the antennas are turned on (see Fig. 2). Thus, all the antenna elements have approximately the same element pattern and thinned arrays are more easily parameterized.

The activation mask is randomly produced at each iteration of the Monte Carlo simulation as follows. First, the lattice is split into four quadrants. Then, starting from the center of the lattice, a probability profile $f(\Delta_y, \Delta_z)$ is defined, where $\Delta_y$ and $\Delta_z$ are the distances of the antenna elements from the center of the lattice in the horizontal and vertical dimensions, respectively. Considering a single quadrant, each element $i = 1, \ldots, N_{\text{quadrant}}$ in position $(y_i, z_i)$ is assigned a value $v_i = u_i \cdot f(y_i, z_i)$, where $\{u_i\}$ are i.i.d. uniform random variables defined in the interval [0,1]. Finally, the elements with the largest values $v_i$ are chosen and the sample quadrant is mirrored over the other three, to force a realistic symmetry. In this paper, a probability profile following an exponential decay $f_y(\Delta_y) = e^{-\alpha_y \Delta_y}$ (and analogously for $f_z$) is chosen.

### B. Scenario Parameters

Specific values and ranges were chosen based on our previous experiences [4], to optimize the positioning of 64 antenna elements over a given lattice. Results shown in Section IV are based on a fixed lattice with $100 \times 99$ antenna elements spaced apart by $d_y, d_z$. Regarding the generation of the activation mask, the probability profile is parameterized by $\alpha_y, \alpha_z \in [-1, 10]$. Values are chosen to allow a very wide
range of possibilities, including extremely sparse ones. Please note that increasing values of $\alpha$ tend to push active antennas together towards the center, while negative values tend to push them towards the outer edges of the lattice.

### III. Framework Definition

The objective of the proposed framework is to greatly restrict the search for an optimal input configuration to a small subspace or, if possible, to find the globally optimal configuration, speeding up simulation-based optimization in the presence of slow simulators. Specifically, in this work, the framework is applied to the network simulator described in Section II. Due to its complexity, using it for a brute-force optimization would be extremely inefficient. Instead, Machine Learning (ML) algorithms are trained to learn the simulator’s input-output relationship. Once the emulator is trained, the network statistics can be computed for any input configuration almost instantaneously. In this way, unseen configurations can be emulated extremely quickly during the optimization phase, thus dramatically reducing the time required for the optimization.

#### A. Data Analysis

A preliminary data analysis is customary in ML problems, as it helps analyze correlations in the given dataset, hinting towards the selection (or exclusion) of some learning algorithms. It can also serve as a sanity check for the optimization results and to discover unexpected data distributions and anomalies.

One of the most basic yet useful tools in high dimensional feature spaces is the correlation plot, i.e., a matrix of scatter plots showing the correlation among variables, as reported in Fig. 3. As expected, some trends are easily recognizable. Nevertheless, visual inspection alone cannot be exhaustive due to the high dimensionality of the input space, nor can the presence of some minima/maxima in the dataset guarantee the global optimality of such points. For research purposes, we generated a total of $N = 1,000$ random configuration, each obtained with 10,000 Monte Carlo iterations.

#### B. Learning Methods

The problem we are facing is a numerical regression on synthetic, noisy data. We recall that the input feature space is a four-dimensional hyperspace where:

- $d_x, d_y$ are the vertical and horizontal spacing, expressed as fractions of $\lambda$;
- $\alpha_x, \alpha_y \in [-1, 10]$ are the probability profile parameters.

The algorithm will predict all the outputs that are required by the optimization process, including the ones used for the constraints. For instance, if one wants to optimize the inputs with respect to variable A (e.g., mean SINR, $\text{SINR}$) while bounding variable B (e.g., minimum coverage requirement on the $5^{\text{th}}$ percentile of the $\text{SINR}$, $\text{SINR}_5$), the emulator must be able to predict both A and B.

Several algorithms were tested, but only a selected subset will be hereby described. The performance of the different techniques is evaluated using 5-fold cross-validation, and, as we are interested in keeping the training set as small as possible, the comparison is made for different training set sizes. Thus, it is possible to know the accuracy of the emulation, based on the number of available samples.

- **Linear regression** is the most basic class of regression algorithms. Despite its simplicity, many versions and adaptations have been created, able to solve non-trivial problems. It is often considered as a baseline for more powerful algorithms. Adding a ridge regularization to the linear regression helps avoid overfitting the training data by imposing a penalty on the size of the weights.
- **Random forests** are ensembles of decision trees, that approximate stepwise the target function;
- **Support Vector Regressors (SVRs)** are derived from the Support Vector Machine (SVM) classification algorithm. Among all the typical kernels, the Gaussian one performed best and is used here.
- **Automatic Relevance Determinations (ARDs)** directly derive from Bayesian Ridge Regression, but includes a sparsity assumption in the priors which stabilizes the weights;
Multi-Layer Perceptron (MLP) is a well-known architecture that should be able to approximate any function. Nevertheless, MLPs generally require (i) long and computationally-demanding hyperparameter tuning and (ii) large datasets. The performance is evaluated using the normalized Root Mean Square Error (nRMSE) metric, as in [3]. Considering a scalar output $y$, the prediction or emulation error is then computed as the difference between the prediction of the emulator $\hat{y}$ and the corresponding simulator output $y$, normalized with respect to the latter, namely

$$\text{nRMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left( y_i - \hat{y}_i \right)^2}$$  \hspace{1cm} (1)

Results are reported in Fig. 4.

IV. OPTIMIZATION RESULTS

The algorithms described in Section III-B were evaluated for increasing dataset sizes. During the creation of the dataset, monitoring the learning performance as the number of available samples increases can help find a plateau of the learning process, allowing to stop the simulations when the required precision is achieved. In fact, the prediction performance is fundamentally limited by the noise in the given dataset, mainly caused by the limited number of Monte Carlo iterations. As the prediction residuals are symmetrically distributed around zero, this should not affect the generalization performance of the model. Based on the comparison of the described algorithms in Fig. 4, we decided to use Random Forests for our emulator as they give the best results even with as few as 500 data points.

The objective function chosen for this problem optimizes the average performance of the given network (mean SINR) while imposing a minimum coverage level, corresponding to a lower bound to the 5th percentile of the SINR as follows

$$\text{maximize} \quad \text{SINR} \hspace{1cm} (2)$$

subject to \quad $\text{SINR}_5 > 6$ dB

Given the description from Section I-A it should be noted that the outcome of this optimization problem does not yield the best possible antenna for the given scenario, but rather a family of antennas following a probability distribution obtained for the optimal parameters $\alpha_y^*, \alpha_z^*$, together with the optimal lattice spacing $d_z^*, d_y^*$.

For comparison, we consider as the baseline antenna an 8×8 UPA with $d_z = d_y = 0.5\lambda$ spacing. Also, we compare the results with the optimal antenna previously found in [3], given by a vertical linear array of 64 elements, with $d_z = 0.79\lambda$.

The ML-based optimization framework suggests as the optimal parameters $\alpha_z^* = 9.02$, $\alpha_y^* = 0.20$, $d_z^* = 0.761$, $d_y^* = 0.866$. To better understand what these parameters suggest, Fig. 5 shows the probability that any given antenna in the lattice is active, together with the corresponding probability profiles. It can be easily noted that the activation probability indicates that vertical antennas tend to perform better than any other configuration, similarly to what was found in our previous work where the 64 × 1 configuration was identified as optimal.

As these results do not identify a specific antenna, but rather a family of antennas, in Fig. 6 we show a comparison between (i) two specific antennas used as references, (ii) antennas generated using non-optimized (i.e., randomly selected) input parameters, and (iii) antennas generated using the optimal ones. Note that, while the antennas from the optimal family do not perform equally, they always achieve significantly better performance with respect to the baseline and to the other configurations and closely approach the optimal antenna found in [3], often improving over the SINR$_5$ although not over the SINR. Though the input parameters optimized by the framework do not directly identify a specific antenna configuration, they allow to drastically reduce the search space to a much narrower area, that can be further explored using more traditional, time-consuming techniques.

Finally, we can study the sensitivity of our optimal point with respect to the four input parameters in Fig. 7. As expected, $\alpha_y^*$ is chosen to be large, forcing the antenna to be vertical. Instead, while a large value of $\alpha_z^*$ would push the elements towards the center to make it less sparse, it...
would also tend to make the antenna more rhomboidal. The optimization was thus able to find the largest possible value for the vertical sparsity that still allowed all antennas to be strictly vertical. Given the preference for a vertical antenna, the horizontal spacing $d_y^*$ is the parameter with the least effects on the network performance. The vertical spacing $d_z^*$ is instead similar to the one previously found.

V. CONCLUSIONS

In this paper, we showed that an ML-based optimization framework can be successfully used to optimize antenna design in a very efficient way. Thanks to the antenna parameterization chosen in this study, our framework was able to explore much more complex configurations than regularly spaced planar arrays. Returning an optimized family of antennas rather than a specific configuration successfully reduces the search space of possible configurations, making it possible to further refine it with more precise simulations. Finally, in a 3GPP-compliant Urban Micro-cell scenario with static users, the optimizer suggests that vertical linear arrays are the optimal configuration, supporting the results of our previous work.

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