Position-Aided Beam Management for Multi-Panel Dynamic Metasurface Antennas

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***Abstract*—Multiple antenna array panels overcome challenges related to hand and body blockage for millimeter wave (mmWave) communication systems. Power consumption, though, increases with the size of the antenna arrays and the number of panels. In this paper, we propose an energy-efficient multi-panel dynamic metasurface antenna (DMA) structure that is not only useful for handsets but also for other applications such as vehicular communications. We propose a location-based ML-aided joint panel and beam management algorithm for the user equipments (UEs) equipped with a multi-panel DMA. This provides a method to select beams and panels with low overhead. The results in vehicular communication settings showed that the proposed beam selection solution for multi-panel DMA performs well and generalizes over different codebooks, antenna sizes, and even orientations and antenna types with the same polarization.**

I. Introduction

In millimeter wave multiple input-multiple output (mmWave MIMO) communication systems, UEs equipped with multi-panel antennas not only provide a way to overcome blockage but also increase the angular coverage. Efficient panel and beam management is vital to avoid the idle power consumption of an active panel [1]. DMAs are slotted antennas with reconfigurable elements, which serve as a low power alternative to a phased array [2], [3]. A multi-panel DMA could provide low-powered beamforming with wide angular coverage. The overhead of selecting an active panel and beamforming weights, however, grows with the number of antenna panels and panel sizes. Therefore, an efficient panel and beam selection for UEs equipped with multi-panel DMAs is required.

Exploiting the UE location to infer beam weights is useful to decrease the overhead of antenna configuration. The prior work involving beam and panel selection mainly focuses on approaches that recommend a subset of beam pairs based on the location [4]–[6]. There is, however, little prior work on beam selection when multiple panels are activated [4]–[6]. In [4], the panel and beam selection was based on the signal power prediction for all beams in all panels, and the predictor was trained using the UE antenna location and orientation. The best UE beam of a single antenna panel was predicted using prior beam power measurements and antenna orientation in [5]. Lastly, the best beam of a UE with a single antenna panel was selected via beam power predictions based on antenna orientation and previous beam measurements, and the method was trained on a large dataset in [6]. The common limitation of [4]–[6] is that the methods are closely tied to specific antenna sizes and codebooks, and do not consider DMAs.

We propose a position-based ML-aided multi-panel UE beam selection method that is agnostic to variations in codebooks, antenna size, antenna orientation, and antenna type between UEs. We call this robustness to the antenna heterogeneity. Our method is trained to predict the incoming signal power over spherical angle grids based on the UE location. The panel and corresponding beam selection are then made based on the angular power prediction given the UE antenna specifics. Our algorithm works for UEs equipped with multiple panels, and is flexible to support the antenna heterogeneity as opposed to [4]–[6]. Moreover, our approach extracts angular power information that is applicable to various antenna configurations. It eliminates the need for data collection for each antenna configuration, ensuring data efficiency. The simulation results for vehicular communication show that our approach effectively configures the beam and panel of a multi-panel DMA, with strong generalization performance.

II. System model

We explain the received signal model with the multi-panel DMA architecture. We then introduce the DMA channel and 3D beamforming solution for a DMA panel.

A. Received signal model

The system consists of a base station (BS) equipped with a uniform planar array (UPA) and a single UE equipped with a multi-panel DMA. We assume a single-stream communication link between the BS and the UE. The UPA at the BS has $N_{\text{t}} = N_{\text{tz}} \times N_{\text{ty}}$ antenna elements controlled by analog phase shifters. The UE has a multi-panel DMA structure with multiple DMA panels, each oriented differently, as shown in Fig. 1. Each panel contains N_{rz} waveguides and N_{ry} radiating slots, yielding a total of $N_{\text{r}} = N_{\text{rz}} \times N_{\text{ry}}$ elements. Let p denote the antenna panel index, $\mathcal{F}$ denote the BS codebok, $\mathcal{W}_p$ denote the codebook of p-th DMA panel, k denote the subcarrier index. We assume an orthogonal frequency-division multiplexing (OFDM) channel $\mathbf{H}_p[k] \in \mathbb{C}^{N_{\text{r}} \times N_{\text{t}}}$ between the p-th panel and the BS at the k-th subcarrier. Let $\mathbf{n}_p[k]$ denote the additive noise, $s[k]$ denote the transmitted symbol at the k-th subcarrier, $\mathbf{w}_{p,n} \in \mathcal{W}_p$ denote the n-th beam of p-th panel, $\mathbf{f} \in \mathcal{F}$ denote a beamformer of the BS. After time and frequency synchronization, the received signal at the p-th panel and k-th subcarrier is expressed as

$$y_{p,n}[k] = \mathbf{w}_{p,n}^* \mathbf{H}_p[k] \mathbf{f} s[k] + \mathbf{w}_p^* \mathbf{n}_p[k]. \tag{1}$$

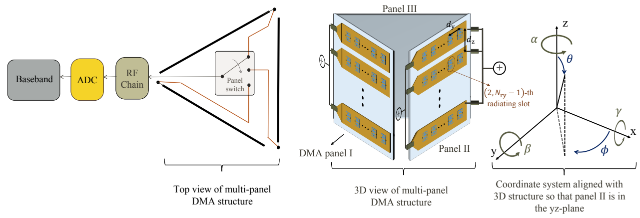

Fig. 1. Multi-panel DMA structure at the UE with panel switching. Each panel has an orientation vector (α, β, γ). The panel II is in the yz-plane, pointing towards +x, and has an orientation of $(0^\circ, 0^\circ, 0^\circ)$ for a reference.

We assume a single DMA panel of the UE is operational at a time through panel switching to receive the signal.

B. DMA channel model and 3D beamforming

We now describe the MIMO channel for p-th DMA panel. It has been shown in [3] that the reconfigurable slots on the DMA can be modeled as magnetic dipoles. The excitation to these dipoles depend on the EM field propagation inside the waveguide. Let $\mathbf{H}_{\mathrm{d}}[k] \in \mathbb{C}^{N_{\mathrm{r}} \times N_{\mathrm{t}}}$ denote the multipath wireless propagation channel with the dipole approximation. The corresponding channel of the z-th waveguide and t-th transmit antenna is $\mathbf{h}_{\mathrm{d},z,t}[k] \equiv [\mathbf{H}_{\mathrm{d}}[k]]_{N_{\mathrm{ry}}(z-1)+1:N_{\mathrm{ry}}z,t} \in \mathbb{C}^{N_{\mathrm{ry}} \times 1}$ for $z = 1, \ldots, N_{\mathrm{rz}}$. The intrinsic DMA waveguide channel is $\mathbf{h}_{\mathrm{dma}}[k] \in \mathbb{C}^{N_{\mathrm{ry}} \times 1}$. Let n_{g} denote the refractive index of the waveguide material, d_{y} and d_{z} denote horizontal and vertical spacing in the Fig. 1, c denote the speed of light, $\odot$ denote the element-wise product, and f denote the frequency at the k-th subcarrier. Assuming that the intrinsic channel is the same for all waveguides and there is no amplitude attenuation, we express it as $\mathbf{h}_{\mathrm{dma}}[k] = e^{-\mathrm{j} n_{\mathrm{g}} \frac{2\pi f}{c} d_{\mathrm{y}}[0:N_{\mathrm{ry}}-1]}$. The effective channel is denoted as $\mathbf{H}_p[k] \in \mathbb{C}^{N_{\mathrm{r}} \times N_{\mathrm{t}}}$ and obtained as

$$
\begin{aligned}
&[\mathbf{H}_p[k]]_{N_{\mathrm{ry}}(z-1)+1:N_{\mathrm{ry}}z,t} = \mathbf{h}_{\mathrm{d},z,t}[k] \odot \mathbf{h}_{\mathrm{dma}}[k], \\
&\text{for } t = 1, \ldots, N_{\mathrm{t}}, \text{ and } z = 1, \ldots, N_{\mathrm{rz}}.
\end{aligned} \tag{2}
$$

This effective channel definition captures the wireless propagation and the intrinsic waveguide phase advance.

We derive a closed-form expression for 3D DMA beamforming weights as an extension to our previous work [7]. The beamforming weights of a DMA antenna follow the Lorentzian constraint as opposed to the unit-modulus constraint that of the phased arrays [3], [7]. In [7], we derive a closed-form solution of the beamforming weights to maximize the line-of-sight beamforming gain for a specific angle and frequency with a single waveguide. Let θ and ϕ denote elevation and azimuth angles. We extend our previous solution to a DMA panel consisting of N_{rz} waveguides by maximizing the beamforming gain $|\mathbf{w}_{\mathrm{DMA}}^T [\mathbf{H}_p[k]]_{:,t}|^2$, where the combiner $\mathbf{w}_{\mathrm{DMA}}$ is subject to the DMA Lorentzian constraint [7]. Before introducing the beamforming solution, we define functions for the weight expression. Let

$$
S_1(\phi, \theta, f) = \frac{\sin\left(\pi N_{\mathrm{ry}} \frac{f}{c} d_{\mathrm{y}} (n_{\mathrm{g}} + \sin\phi \sin\theta)\right)}{\sin\left(\pi \frac{f}{c} d_{\mathrm{y}} (n_{\mathrm{g}} + \sin\phi \sin\theta)\right)}, \tag{3}
$$

and,

$$
S_2(\phi, \theta, f) = \frac{\sin\left(\pi N_{\mathrm{rz}} \frac{f}{c} d_{\mathrm{z}} \cos\theta\right)}{\sin\left(\pi \frac{f}{c} d_{\mathrm{z}} \cos\theta\right)}. \tag{4}
$$

Let $\mathrm{sgn}(\cdot)$ denote the signum function. We define the reconfigurable phase $\mathcal{V}_{z,y}(\phi, \theta, f)$ for the DMA beamforming as

$$
\begin{aligned}
\mathcal{V}_{z,y}(\phi, \theta, f) = &-\frac{\pi}{2} + \mathrm{sgn}(S_1(\phi, \theta, f) S_2(\phi, \theta, f)) \\
&+ \frac{2\pi f}{c} \left[d_{\mathrm{y}} (n_{\mathrm{g}} + \sin\theta \sin\phi) \left(y - 1 - \frac{N_{\mathrm{ry}} - 1}{2} \right) \right. \\
&\left. + d_{\mathrm{z}} \cos\theta \left(z - 1 - \frac{N_{\mathrm{rz}} - 1}{2} \right) \right].
\end{aligned} \tag{5}
$$

Let $[\mathbf{w}_{\mathrm{DMA}}]_{z,y}$ denote the beamforming weight for y-th radiating slot on the z-th waveguide. The beamforming weight, maximizing the beamforming gain at the target (θ, ϕ, f), is

$$
[\mathbf{w}_{\mathrm{DMA}}]_{z,y} = \frac{-\mathrm{j} + e^{\mathrm{j} \mathcal{V}_{z,y}(\phi, \theta, f)}}{2}, \tag{6}
$$

which satisfies the Lorentzian constraint [3]. This beamforming design is optimal only for directive beams whereas the optimal codebook design for arbitrary beam shaping is a future research direction.

III. Joint multi-panel beam management

We first define the multi-panel beam management problem. We next introduce the proposed solution for the problem.

A. Problem formulation

In this paper, we consider the problem of jointly selecting the panel index p and the combiner $\mathbf{w}_{p,n}$ over all combiners across all panels. Let P denote the number of panels at the UE. The total number of UE combiners is $\sum_{p=1}^{P} |\mathcal{W}_p|$. The BS has $|\mathcal{F}|$ beamformers, and then the total number of beam pairs is $|\mathcal{F}| \sum_{p=1}^{P} |\mathcal{W}_p|$. Without any beam selection, the search space is too large to configure the BS beamformer, UE panel and combiner. In our prior work [8], we showed that it is possible to configure the analog BS beamformer independently from the analog UE combiner. In this paper, we assume that the optimal analog BS beamformer $\mathbf{f}^\star$ maximizing the downlink received signal power is known. The joint panel index and combiner selection is over the smaller set of panel and combiner pairs $\{(n, p) : \forall \mathbf{w}_n \in \mathcal{W}_p \text{ and } \forall p \in \{1, .., P\}\}$. We consider the subset selection over this set instead of a single panel and combiner selection since a single selection might not achieve high signal power in a highly dynamic environment. The selected subset $\mathcal{S}$ decreases the search space further for beam sweeping. Let K denote the subset size $|\mathcal{S}|$, $\mathsf{P}_{p,n} = \sum_k |y_{p,n}[k]|^2$ denote the received signal power for (n, p)-th panel combiner pairs. The subset selection is formulated as

$$
\mathcal{S} = \mathrm{argsort}\left(\{\mathsf{P}_{p,n} : \forall p, \mathbf{w}_n \in \mathcal{W}_p\}, \text{ desc}\right)[1:K]. \tag{7}
$$

Based on (7), the main problem is to develop a method that predicts the received signal power for all panel-combiner pairs based on the UE location and antenna heterogeneity.

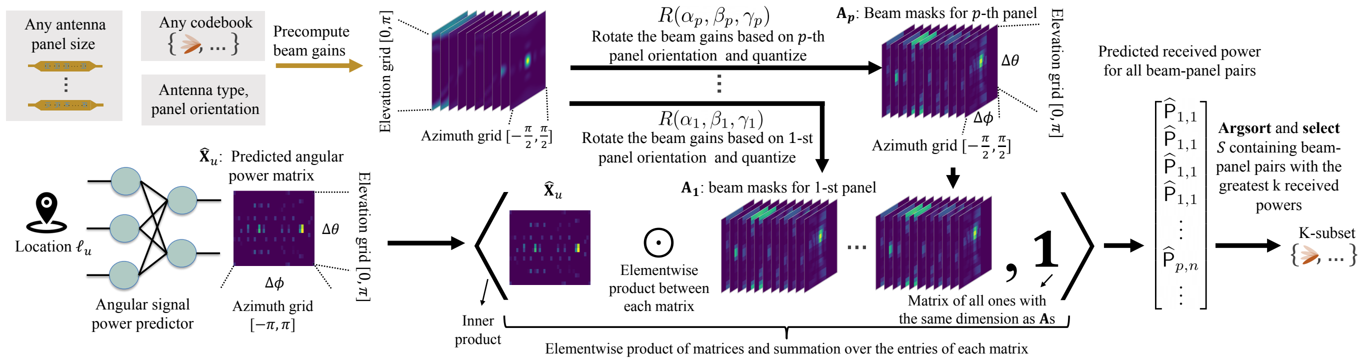

Fig. 2. Proposed antenna heterogeneity-agnostic multi-panel DMA beam management.

B. Heterogeneity-agnostic panel and beam selection

We propose a panel and beam selection method designed to accommodate heterogeneous UE antenna configurations, including differences in codebook type, antenna size, orientation, and element pattern. Using (7), the goal is to predict the received signal power for all panel-combiner pairs while performing across diverse structures. To achieve this, we leverage the notion of power angular spectrum (PAS), which expresses the received power as a function of azimuth and elevation angles from the receiver's perspective [9]. The PAS of a receiver at particular location is independent of the receiver's antenna structure or beam configuration but depends only on the environment. The received signal power for a particular beam can be approximated through integration of the product of the beam gain and the PAS over the angular range [9]. Based on this, we approximate PAS on a discrete angular grid, which we define as angular power grid, to predict received powers for any combiner of any antenna configuration.

We formally introduce the angular power grid and how to obtain the signal power for a specific panel combiner. Let $[-\pi, \pi]$ and $[0, \pi]$ denote the ranges of azimuth and elevation angles, M_ϕ, M_θ denote the number of azimuth and elevation grids, $\Delta\phi$ and $\Delta\theta$ denote the uniform angular range in azimuth and elevation of each angular grid. We denote the angular signal power matrix, named as angular power matrix, for the u-th UE location $\boldsymbol{\ell}_u = [\mathrm{x}, \mathrm{y}, \mathrm{z}]$ as $\mathbf{X}_u \in \mathbb{R}_{\geq 0}^{M_\theta, M_\phi}$, it is non-negative and each entry represents the average signal power within a grid. Let $(\alpha_p, \beta_p, \gamma_p)$ denote the orientation of the p-th DMA panel, where $(\alpha_p, \beta_p, \gamma_p)$ are rotations around (z, y, x) axis as in the Fig. 1. We introduce the concept of beam mask, that is the total beam gain in each angular grid. Let $\mathrm{AF}_{p,n}(\theta, \phi)$ denote the beam pattern of n-th beam of p-th panel (refer to [10] for details), where $\theta \in [0, \pi]$, $\phi \in [-\pi/2, \pi/2]$ for $(\alpha_p, \beta_p, \gamma_p) = (0°, 0°, 0°)$. $\mathrm{AF}_{p,n}(\theta, \phi)$ is set to zero for $\phi \in [-\pi, -\pi/2] \cup [\pi/2, \pi]$ so that $\mathrm{AF}_{p,n}(\theta, \phi)$ covers entire spherical angles. Let $R_{\alpha,\beta,\gamma}(\theta, \phi)$ denote the spherical angle transformation function over the unit sphere for the antenna orientation (α, β, γ) with respect to $(\alpha, \beta, \gamma) = (0°, 0°, 0°)$ as described in [11]. $R_{\alpha,\beta,\gamma}(\theta, \phi)$ generates the transformed spherical angles over the unit sphere. Let (m_θ, m_ϕ) denote the indices of angular grid, $\mathbf{A}_{p,n}$ denote the beam mask of the p-th panel and n-th beam, (m_θ, m_ϕ) denote the grid indices, C denotes the angular region of the grid $\{(\theta, \phi) : \theta \in [(m_\theta - 1)\Delta\theta, m_\theta\Delta\theta], \phi \in [(m_\phi - 1)\Delta\phi, m_\phi\Delta\phi]\}$. The total beam gain over the grid region C is calculated as

$$[\mathbf{A}_{p,n}]_{(m_\theta, m_\phi)} = \iint_C |\mathrm{AF}_{p,n}(R^{-1}{}_{\alpha_p,\beta_p,\gamma_p}(\theta, \phi))|^2 \sin\theta \, d\phi d\theta, \tag{8}$$

where the integral is taken over the surface of a unit sphere. The signal power for p-th panel and n-th beam at the location $\boldsymbol{\ell}_u$ is obtained as

$$\mathsf{P}_{p,n} = \langle \mathrm{vec}(\mathbf{X}_u), \mathrm{vec}(\mathbf{A}_{p,n}) \rangle. \tag{9}$$

Given an angular power matrix $\mathbf{X}_u$, the received signal power for any combiner can be calculated through (9).

We formulate an optimization problem to obtain the angular powers over the locations. We assume that the BS has a collection of measured received powers for beams in the codebooks of all UE DMA panels over different UE locations. Let $\mathbf{p}_u$ denote the received power measurement vector $\left[\mathsf{P}_{1,1}, \ldots, \mathsf{P}_{p,|\mathcal{W}_p|}\right]^{\mathrm{T}}$, $\mathbf{A}$ denote the collection of beam masks corresponding to all beams $\left[\mathrm{vec}(\mathbf{A}_{1,1}), \ldots, \mathrm{vec}(\mathbf{A}_{p,|\mathcal{W}_p|})\right]$. The constrained convex optimization problem to find angular power matrix for the UE location $\boldsymbol{\ell}_u$ is constructed as

$$\mathbf{X}_u^\star = \underset{\mathbf{X}_u, \forall [\mathbf{X}]_{i,j} \geq 0}{\arg\min} \|\mathrm{vec}(\mathbf{X}_u)^{\mathrm{T}}\mathbf{A} - \mathbf{p}_u^{\mathrm{T}}\|_2^2. \tag{10}$$

We use the CVX solver to obtain the angular power matrix $\mathbf{X}_u^\star$, minimizing the squared error of reconstructing the measured signal power through proposed methodology [12].

We formulate the angular power prediction as a multi-output regression over UE location, as each angular grid is continuous. The angular powers corresponding to each UE location are obtained by (10), resulting in a labeled training dataset of $(\boldsymbol{\ell}_u, \mathbf{X}_u^\star)$ pairs. While a UE could use this dataset to predict the received power for its combiners, which is not practical, the UE only needs data near its location. To address this, we train a multi-output regression model that predicts angular power for a given location $\boldsymbol{\ell}_u$, allowing the model to leverage information from all locations while minimizing the data size offloaded to the UE via a sidelink connection.

The proposed method works as shown in Fig. 2. Initially, the UE precomputes beam gains at high resolution over spherical angles for the codebooks of each DMA panel with $(\alpha, \beta, \gamma) = (0^\circ, 0^\circ, 0^\circ)$. This offline calculation avoids regenerating beam masks via (8) in real time for frequent orientation changes. During online operation, the UE obtains its location $\boldsymbol{\ell}_u$ from localization sensors and uses the angular gain predictor to generate the angular power matrix $\widehat{\mathbf{X}}_u$. The UE also measures the orientation (α, β, γ) of each panel via sensors such as a gyroscope and applies the orientation transformation $R_{\alpha,\beta,\gamma}(\theta, \phi)$ in [11] to precomputed beam gains. The beam gains in (8) within each angular grid are approximated by a double summation. Finally, the predicted received power $\widehat{\mathsf{P}}_{p,n}$ for each panel-combiner pair is obtained using (9), and panel and combiner subset selection is performed using (7).

IV. Performance evaluation

We introduce the performance evaluation of the proposed UE panel and beam management. We first describe the simulation environment. We then introduce performance metrics and the benchmark. We finally show the simulation results.

A. Realistic channel generation and offline training

Realistic channel generation is essential for evaluating the performance of data-driven wireless solutions. To achieve this, we rely on spatially consistent ray-traced channel data in Sionna [13] for dynamic vehicular scenarios. The evaluation considers a vehicular communication system in a 300 m $\times$ 200 m urban canyon with 8 roads, using cars as UEs and buses as dynamic blockers, created based on the methodology in [8]. The BS, equipped with an 8×8 UPA with horizontally placed dipole elements using DFT codebooks, is mounted on a building wall at 15 meters height, while the UE multi-panel DMAs are placed on car roofs at 1.5 meters height. Each UE has 3 DMA panels with orientations $(\alpha_p, \beta_p, \gamma_p) = (0, 0, 30^\circ + (p-1)120^\circ)$, ensuring no polarization angle changes across panels. The carrier frequency is 15 GHz, and the system bandwidth of 1.8 GHz is treated as frequency-flat for the DMA beamformers. The average speed of the UEs is 9 m/s. Channels are generated under these settings for a comprehensive analysis of the proposed method.

Channels are used to create an angular gain matrix dataset, beam masks, and to train the angular power predictor. We generate channels for 9 episodes, each featuring varied car and bus initializations. Sampling occurs every 100 ms over 10 s per episode, resulting in 18000 diverse channel samples. The angular grid and beam mask resolutions are set to $\Delta\theta$ and $\Delta\phi$ of 10°. For the learning model, we use XGBoost Regressor, which excels in multi-output regression tasks as in [8], [14]. We allocate 80% and 20% of the samples for training and testing, maintaining a total parameter count under 200K at 64-bit precision.

B. Received power loss, misalignment, and benchmark

Extensive simulation and relevant comparison are necessary to assess the performance of the proposed method. There is no direct comparison benchmark to our proposed method that generalizes to multi-panels with different orientations, different codebooks, and antenna sizes. We, therefore, compare our method to a closely related benchmark in terms of orientation and multi-panel proposed for indoor beam selection in [4]. The benchmark consists of a beam power predictor whose inputs are location and orientation vectors and the outputs are predicted power for beams. Therefore, the model is specifically tied to an antenna size and codebooks.

We use two performance metrics: power ratio and misalignment probability. The power ratio compares the maximum signal power obtained by the chosen panel and beam subset $\mathcal{S}_u$ for the uth test point with the maximum signal power across all panel and beam pairs. Let M denote the number of test samples, then power ratio R_p is given as

$$R_\mathrm{p} = \frac{1}{M} \sum_{u=1}^{M} \frac{\max\limits_{(p,n) \in \mathcal{S}_u} \mathsf{P}_{p,n}}{\max \mathbf{p}_u}. \qquad (11)$$

The power ratio is plotted in dB scale and can be interpreted as the power loss of not choosing the best panel and beam pair in dB. The second metric is misalignment probability. The misalignment probability is the probability of not selecting the best panel and beam pair (refer to [8] for details).

C. Achieving heterogeneity-agnostic panel and beam selection

The main advantage of our work is to have a multi-panel beam management method that can work with various antenna panels, antenna sizes, codebooks, and even antenna types, provided the polarization mismatch remains consistent. Fig. 3 illustrates the power loss in red curves and misalignment probability in blue curves across increasing percentages of selected subset size to all panel and beam pairs, calculated as $K/(\sum_{p=1}^{L} |\mathcal{W}_p|) \times 100$. A UPA has dipole elements with horizontal polarization. UPA codebooks are DFT codebooks, and DMA codebooks are calculated via (6) over uniform azimuth and elevation angles in $[-120^\circ, 120^\circ]$ and $[30^\circ, 150^\circ]$. The proposed method is trained on 5×5 multi-panel DMA and tested on 3×3, 4×4, 5×5 multi-panel DMAs and UPAs. The baseline is also trained and tested for 5×5 multi-panel DMAs. Fig. 3 shows that our approach performs better than the baseline in selecting 10% of all panel and beams in terms of misalignment and power loss and the same in selecting more. Proposed method generalizes for all other antenna sizes, types and codebooks and achieves less than 2 dB power loss at least selecting 13% of all panel and beam pairs. Misalignment exhibits greater variability across DMA test cases because DMA beams have stronger side lobes in addition to the main lobe. This makes minimizing misalignment more challenging for DMA beams. The proposed solution, however, achieves strong generalization performance in handling antenna-heterogeneity under power loss as well as misalignment probability.

Fig. 4 represents the empirical CDF of power loss in dB of the proposed method trained on 5×5 DMA. The CDF is calculated for selecting 10% of all panel and beam pairs for 3600 UEs. Fig. 4 shows user-for-user power loss performance

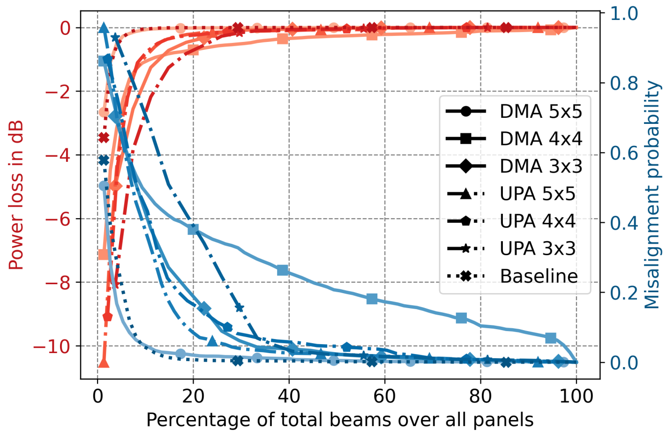

Fig. 3. Received power loss and misalignment probability compared to the best panel and beam. The proposed method trained on the measurements from the multi-panel 5×5 DMA achieves at most 2 dB power loss at selecting 13% of all panel and beam pairs and provides a good generalization performance.

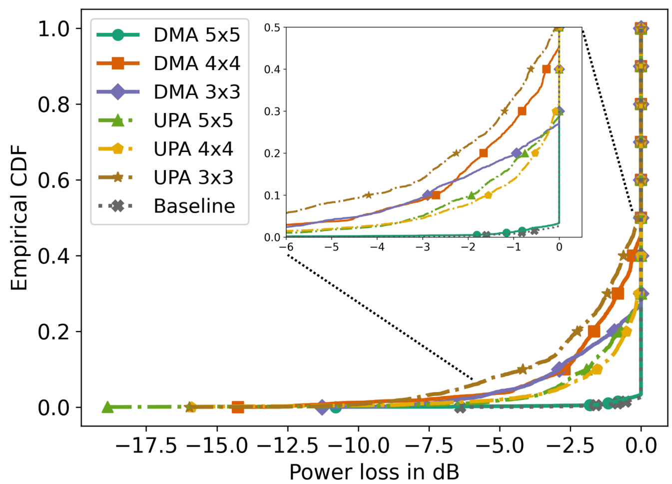

Fig. 4. Empirical CDF of power loss of selecting 10% of all panel and beam pairs. The proposed method is trained on multi-panel 5×5 DMA and tested on 3×3, 4×4, 5×5 multi-panel DMAs and UPAs. The proposed method provide 2.5 dB loss at the worst case for 85% of the users with the possibility of 0 dB loss.

of the proposed system. Our method is able to achieve at most 2 dB power loss for at least 80% of all possible UEs for all test cases with different antenna sizes, codebooks and antenna types. The proposed method specifically performs the same when tested on the same configuration, however, it introduces the possibility of 2 dB power loss in antenna-heterogeneity. In short, the generalization of the proposed method without any further training for antenna heterogeneity seems promising.

V. Conclusion

We proposed a location-based ML-aided beam management system for UEs with multi-panel DMAs. The proposed management approach is agnostic to antenna heterogeneity, including panel size, codebook, orientation, and antenna type with fixed polarization mismatch. We evaluated our approach through extensive, realistic simulations in a high-mobility vehicular communication scenario with high blockage probability. The simulation results showed out that the proposed solution performs comparably to the baseline while generalizing across antenna sizes, codebooks, and types with a small error margin. Our approach holds promise for beam management in UEs with multi-panel DMAs, offering low-power beamforming solutions. Future work will focus on optimizing DMA codebooks and extending the model to account for polarization effects that change with orientation and antenna patterns, applicable to handsets with rapid orientation changes.

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