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Failure Tolerant Phase-Only Indoor Positioning via Deep Learning

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Abstract—High-precision localization turns into a crucial added value and asset for next-generation wireless systems. Carrier phase positioning (CPP) enables sub-meter to centimeter-level accuracy and is gaining interest in 5G-Advanced standardization. While CPP typically complements time-of-arrival (ToA) measurements, recent literature has introduced a *phase-only* positioning approach in a distributed antenna/MIMO system context with minimal bandwidth requirements, using deep learning (DL) when operating under ideal hardware assumptions. In more practical scenarios, however, antenna failures can largely degrade the performance. In this paper, we address the challenging phase-only positioning task, and propose a new DL-based localization approach harnessing the so-called hyperbola intersection principle, clearly outperforming the previous methods. Additionally, we consider and propose a processing and learning mechanism that is robust to antenna element failures. Our results show that the proposed DL model achieves robust and accurate positioning despite antenna impairments, demonstrating the viability of data-driven, impairment-tolerant phase-only positioning mechanisms. Comprehensive set of numerical results demonstrates large improvements in localization accuracy against the prior art methods.

Index Terms—6G, carrier phase positioning, cell-free, deep learning, distributed MIMO, hardware impairments, integer ambiguities, neural networks.

I. INTRODUCTION

The 3rd Generation Partnership Project (3GPP) Release 17 and 18 standards have introduced stringent positioning requirements, targeting centimeter-level accuracy [1], [2]. As a result, high-precision positioning has become a key feature in next-generation terrestrial mobile communication systems. *Carrier phase positioning (CPP)* is well known for enabling precise ranging, achieving sub-meter to centimeter-level accuracy [3]. While CPP techniques have been widely employed in the global navigation satellite system (GNSS) context [4], their adoption in 3GPP standardization has gained traction, particularly within 5G-Advanced, where carrier phase measurements are being explored as an emerging technology to enhance positioning capabilities [5]. To this end, the CPP mechanisms have been investigated for 5G networks using different reference signals, such as positioning reference signal (PRS) [6], [7] and demodulation reference signal (DMRS) [8], further demonstrating their potential in cellular-based

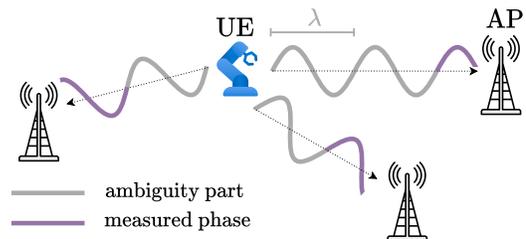


Fig. 1. Illustration of uplink UE positioning with distributed phase-coherent antenna points (APs) where only the carrier phase measurements at different APs are used to estimate the UE position.

positioning. Additionally, extracting highly accurate situational awareness is also expected to be a key asset in future 6G networks [5].

In general, the available CPP techniques mostly utilize phase measurements as an additional asset or measurement, complementing the more ordinary time-of-arrival (ToA) or time-difference-of-arrival (TDoA) positioning measurements [2], [3], [6], [9]. Alternatively, [10] has recently proposed a *phase-only* user equipment (UE) positioning approach in distributed phase-coherent multiple-input multiple-output (MIMO) systems by introducing two deep learning (DL) solutions that use only uplink carrier phase data while operating under a perfect hardware assumption. This scenario is conceptually illustrated in Fig. 1, and also forms the main overall scope of this work.

In practical implementations, antenna elements are vulnerable to failures caused by hardware aging, environmental conditions, or catastrophic events [11]. Beyond hardware impairments, as observed particularly in multi-antenna GNSS receivers, spoofing attacks can introduce additional performance-degrading impairments [12], [13]. In such scenarios, data-driven learning-based methods offer a promising alternative by enabling systems to learn robust representations directly from observed data, without relying on explicit system modeling. These methods have shown increasing potential in adapting to complex and imperfect conditions [14]–[17]. While early studies focused on communication-oriented tasks [14], recent work demonstrates the applicability of data-driven techniques

to sensing and localization, where resilience to different types of hardware and other impairments is essential [16].

In this paper, we address the challenging phase-only positioning task, via deep learning, with the primary purpose of improving the localization accuracy beyond that offered by the existing state-of-the-art approach in [10]. Furthermore, motivated by the above practical impairment considerations, we investigate and extend the phase-only positioning approach to scenarios involving antenna element failures. Specifically, we propose and present a neural network (NN) model trained on data from both fault-free and antenna failure conditions to improve robustness against hardware impairments. Additionally, we employ a novel, so-called hyperbola intersection method, leveraging phase differences as the primary input modality for position estimation. Our numerical results show that the proposed method achieves sub-centimeter accuracy, with 95th percentile errors consistently below 2 cm across various transmit powers and failure probabilities in the considered evaluation environment. Additionally, we demonstrate that including failure scenarios during training significantly improves the considered NN model's ability to adapt to antenna faults, enabling reliable and precise positioning even under practical failure conditions. These results validate the effectiveness of the proposed learning-based phase-only positioning framework in real-world, imperfect distributed antenna environments.

II. SYSTEM MODEL

Similar to [10], we consider an uplink scenario involving a UE and I distributed, mutually phase-synchronized antenna points (APs). Fig. 1 depicts an example scenario involving three APs such that $I = 3$. The UE has an unknown position denoted by $\mathbf{x}_{\text{ue}} \in \mathbb{R}^2$, while the positions of the APs are known and represented as $\mathbf{x}_{\text{ap},i} \in \mathbb{R}^2$ for $i \in \{0, \dots, I-1\}$. For simplicity and brevity, the analysis is restricted to line-of-sight (LoS) propagation conditions, while the extensions to multipath scenarios and three-dimensional space, i.e., \mathbb{R}^3 form an important topic for our future work.

The UE transmits a unit-power narrowband pilot symbol, denoted as s , with a transmit power P_T where its bandwidth is equal to W . The received signal at the i -th AP over the LoS path is given by

$$y_i = f_i \sqrt{P_T/W} \rho_i \exp\left(-j\left(\frac{2\pi}{\lambda}d_i - \phi_{\text{ue}}\right)\right) s + v_i, \quad (1)$$

where ρ_i denotes the path loss between the UE and the i -th AP, λ is the wavelength, $d_i = \|\mathbf{x}_{\text{ue}} - \mathbf{x}_{\text{ap},i}\|$ is the Euclidean distance between the UE and the i -th AP, ϕ_{ue} represents the common phase offset between the UE and the AP network, and $v_i \sim \mathcal{CN}(0, N_0)$ denotes additive complex Gaussian noise. The binary indicator $f_i \in \{0, 1\}$ models hardware-related failures at the i -th AP, where $f_i = 1$ indicates operational status and $f_i = 0$ represents failure. We assume that each AP fails independently with probability p_f . By processing y_i , the resulting phase observation can be

expressed as

$$\theta_i = f_i \times \left(-\frac{2\pi}{\lambda}d_i + \phi_{\text{ue}} + 2\pi z_i\right) + n_i, \quad (2)$$

where $z_i \in \mathbb{Z}$ is the integer ambiguity, and $n_i \sim \mathcal{N}(0, \sigma_i^2)$ models phase measurement noise. Using (2), one specific AP is assigned as a reference unit by the network, e.g., $i = 0$, and we define the differential measurements for $m \in \{1, \dots, I-1\}$ as

$$\delta_m = -\frac{\lambda}{2\pi}(\theta_m - \theta_0) \quad (3)$$

$$= \Delta d_m - \lambda \Delta z_m - \frac{\lambda \phi_{\text{ue}}}{2\pi} \Delta f_m + \Delta n_m, \quad (4)$$

where $\Delta d_m = f_m d_m - f_0 d_0$, $\Delta z_m = f_m z_m - f_0 z_0$, $\Delta f_m = f_m - f_0$ and $\Delta n_m = (\lambda/2\pi)(n_m - n_0)$. Also, we define the failure-independent counterpart of Δd_m and Δz_m as $\Delta \bar{d}_m = d_m - d_0$ and $\Delta \bar{z}_m = z_m - z_0$, respectively. Stacking the differential measurements in (4), we obtain the vector $\boldsymbol{\delta} = [\delta_1, \dots, \delta_{I-1}]^\top$.

When $f_m = f_0 = 1$, the term δ_m geometrically defines a collection of hyperbolas parameterized by Δz_m , where the foci are located at $(\mathbf{x}_{\text{ap},m}, \mathbf{x}_{\text{ap},0})$. Failure of the reference AP compromises all elements of the differential measurements, thereby increasing the difficulty of the positioning task.

III. PROPOSED HYPERBOLA INTERSECTION METHOD

In this section, we present the proposed hyperbola intersection method, which integrates DL and gradient descent (GD) techniques to estimate the position of the UE using the above phase-based measurements while also detecting AP failures. The overall framework is illustrated in Fig. 2 and consists of two main components: a differential ambiguity estimator based on a multi-layer perceptron (MLP), and a GD-based solver. The GD-based solver outputs an estimated UE position denoted by $\hat{\mathbf{x}}_{\text{ue}}$, along with the final cost value E_T . The computed cost value E_T serves as a confidence level for the position estimate $\hat{\mathbf{x}}_{\text{ue}}$. If the cost satisfies $E_T \leq \tau$, where τ is a predefined threshold, the framework flags *No AP Failure*, indicating the position estimation is considered reliable. Otherwise, it flags a *Potential AP Failure*, detecting a potential failure in one or more APs.

A. NN-based Differential Ambiguity Estimator

A key challenge to achieving reliable CPP lies in the resolution of *integer ambiguities* [18]. To address this issue, an MLP-based neural network model is introduced to generate a vector of failure-independent differential ambiguity estimates $\Delta \hat{\mathbf{z}} = [\Delta \hat{z}_{j_1}, \dots, \Delta \hat{z}_{j_{|\mathcal{J}|}}]^\top$ from the differential measurements $\boldsymbol{\delta}$, where $\mathcal{J} = \{j_k\}_{k=1}^{|\mathcal{J}|} \subseteq \{1, 2, \dots, I-1\}$ denotes the set of AP indices whose failure-independent differential ambiguities are estimated, with the cardinality of $|\mathcal{J}|$. Here, $\Delta \hat{z}_{j_k}$ denotes the estimate of $\Delta \bar{z}_{j_k}$.

Each failure-independent differential ambiguity $\Delta \bar{z}_{j_k}$ is constrained within the geometric bounds $[-q_{j_k} - 1, q_{j_k}] = [\lceil -\|\mathbf{x}_{\text{ap},j_k} - \mathbf{x}_{\text{ap},0}\|/\lambda \rceil, \lfloor \|\mathbf{x}_{\text{ap},j_k} - \mathbf{x}_{\text{ap},0}\|/\lambda \rfloor]$, where $\lceil \cdot \rceil$ represents the floor function, which yields the greatest integer

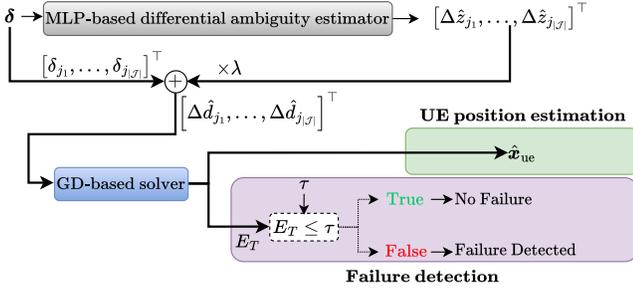


Fig. 2. Framework of the proposed approach.

less than or equal to the input. Consequently, each differential ambiguity can take $Q_{j_k} = 2q_{j_k} + 2$ possible labels, and the combined number of possible labels for the differential ambiguities in the set \mathcal{J} is given by $Q = \sum_{k=1}^{|\mathcal{J}|} Q_{j_k}$.

The architecture of the proposed MLP model is illustrated in Fig. 3. The input is first processed by shared layers, followed by $|\mathcal{J}|$ parallel branches. Both the shared layers and the initial layer of each parallel branch employ the Rectified Linear Unit (ReLU) activation function. The second layer of each branch uses the softmax activation function to produce a probability distribution $\mathbf{p}_{j_k} = [p_{j_k, -q_{j_k}-1}, \dots, p_{j_k, q_{j_k}}]^T$, where each element $p_{j_k, l} \in [0, 1]$ represents the probability of $\Delta \bar{z}_{j_k}$ taking the integer value l , satisfying $\sum_l p_{j_k, l} = 1$. To obtain the final integer ambiguity prediction, each probability distribution is passed through an argmax function which selects the most probable class for each differential ambiguity. This results in the estimate $\Delta \hat{z}_{j_k} = \arg \max_{l \in [-q_{j_k}-1, q_{j_k}]} p_{j_k, l}$. The sparse categorical cross-entropy [19] is employed as the loss function to train the MLP model. By noting that $p_{j_k, \Delta \bar{z}_{j_k}}$ is the generated probability of the correct label for \bar{z}_{j_k} , the loss function can be expressed as

$$\mathcal{L}_{\text{SCCE}} = -\frac{1}{|\mathcal{J}|} \sum_{k=1}^{|\mathcal{J}|} \ln(p_{j_k, \Delta \bar{z}_{j_k}}), \quad (5)$$

where $\ln(\cdot)$ is the natural logarithm. Finally, as illustrated in Fig. 2, the estimated ambiguities, scaled with λ , are added to the corresponding differential phase measurements to obtain the failure-independent differential distance estimations

$$\begin{aligned} [\Delta \hat{d}_{j_1}, \dots, \Delta \hat{d}_{j_{|\mathcal{J}|}}]^T &= [\delta_{j_1}, \dots, \delta_{j_{|\mathcal{J}|}}]^T \\ &+ \lambda [\Delta \hat{z}_{j_1}, \dots, \Delta \hat{z}_{j_{|\mathcal{J}|}}]^T. \end{aligned} \quad (6)$$

B. Gradient Descent-Based Solver

We propose an iterative GD-based optimization algorithm for joint UE positioning and AP failure detection. The algorithm is initialized with a random initial guess $\mathbf{x}_{\text{ue},0}^{(\text{GD})}$ for the UE position. At each iteration $t \in \{1, 2, \dots, T\}$, the Euclidean distance from the current UE position estimate $\mathbf{x}_{\text{ue},t}^{(\text{GD})}$ to the j_k -th AP is computed as $d_{j_k,t}^{(\text{GD})} = \|\mathbf{x}_{\text{ue},t}^{(\text{GD})} - \mathbf{x}_{\text{ap},j_k}\|$. Also, we compute the Euclidean distance from the current UE position estimate to the reference AP as $d_{0,t}^{(\text{GD})} = \|\mathbf{x}_{\text{ue},t}^{(\text{GD})} - \mathbf{x}_{\text{ap},0}\|$. Differential distances with respect to the reference AP are then formed as $\Delta d_{j_k,t}^{(\text{GD})} = d_{j_k,t}^{(\text{GD})} - d_{0,t}^{(\text{GD})}$. These are compared with

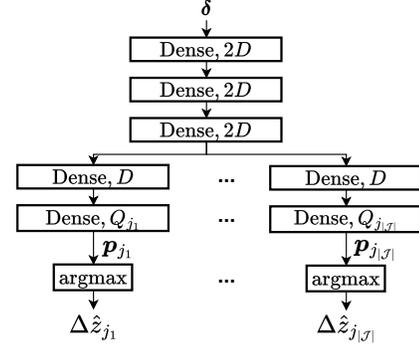


Fig. 3. Architecture of the proposed MLP-based ambiguity estimation approach: Each rectangle denotes a dense (fully connected) layer, with the number inside indicating the neuron count and each branch outputs a failure-independent differential ambiguity estimation.

the differential distances $\Delta \hat{d}_{j_k}$ predicted by the MLP-based ambiguity estimator, which remains fixed during iterations. The residual errors are computed as $e_{j_k,t} = \Delta d_{j_k,t}^{(\text{GD})} - \Delta \hat{d}_{j_k}$. These residuals are used to define the quadratic cost function $E_t = \sum_{k=1}^{|\mathcal{J}|} (e_{j_k,t})^2$. The position estimate is updated according to $\mathbf{x}_{\text{ue},t+1}^{(\text{GD})} = \mathbf{x}_{\text{ue},t}^{(\text{GD})} - \alpha \nabla E_t$, where α is the learning rate and ∇E_t denotes the gradient of the cost function with respect to $\mathbf{x}_{\text{ue},t}^{(\text{GD})}$, given by

$$\nabla E_t = 2 \sum_{k=1}^{|\mathcal{J}|} e_{j_k,t} \left(\frac{\mathbf{x}_{\text{ue},t}^{(\text{GD})} - \mathbf{x}_{\text{ap},j_k}}{d_{j_k,t}^{(\text{GD})}} - \frac{\mathbf{x}_{\text{ue},t}^{(\text{GD})} - \mathbf{x}_{\text{ap},0}}{d_{0,t}^{(\text{GD})}} \right). \quad (7)$$

After completing T iterations, the final UE position estimation $\hat{\mathbf{x}}_{\text{ue}} = \mathbf{x}_{\text{ue},T}^{(\text{GD})}$ and the final cost E_T are generated. The framework generates a *No AP Failure* flag when $E_T \leq \tau$, which indicates that the estimated position $\hat{\mathbf{x}}_{\text{ue}}$ can be considered reliable. Conversely, if $E_T > \tau$, the framework outputs a *Potential AP Failure* flag, indicating either an incorrect estimation of differential ambiguities by the MLP-based ambiguity estimator or a potential AP failure. In this work, we interpret the threshold test primarily as an AP failure detection mechanism; thus, $E_T > \tau$ is taken as an indication of a potential AP failure. It is important to note that the proposed solver always outputs a UE position estimate $\hat{\mathbf{x}}_{\text{ue}}$, regardless of the final cost E_T ; that is, no position estimate is discarded, even when $E_T > \tau$. The choice of τ critically affects the failure detection performance: a smaller τ improves sensitivity to potential AP failures but may erroneously reject reliable estimates, while a larger τ increases tolerance to estimation errors at the risk of missing actual failures.

IV. INFERENCE COMPLEXITY

We next assess the inference complexity of both components of the proposed approach: the NN-based differential ambiguity estimator and the GD-based solver. The computational cost is measured using the floating-point operation (FLOP) count [20]–[25], where each elementary arithmetic operation (addition, subtraction, multiplication, division, square root) counts as one FLOP, following the approach established in [23]–[25].

A. Inference Complexity of the Proposed NN-based Differential Ambiguity Estimator

The computational complexity of a fully connected layer with n_i inputs and n_o outputs is approximately $n_o(2n_i - 1) \approx 2n_o n_i$ FLOPs, where bias additions and activation functions contribute negligibly to the overall cost for large layers. Since the NN-based ambiguity estimation model described in Section III-A consists exclusively of fully connected layers, the total inference complexity can be estimated as $\mathcal{C}_{\text{NN}} \approx D^2(4|\mathcal{J}| + 16) + D(2Q + 4I)$ FLOPs, where the computational overhead of the argmax operation is considered negligible and thus omitted from this analysis.

B. Inference Complexity of the Proposed Gradient Descent-based Solver

In each iteration, the distance calculations between the current UE position and the selected APs involve $6|\mathcal{J}| + 6$ FLOPs, while the differential distance calculations consume $|\mathcal{J}|$ FLOPs and the error calculations need $|\mathcal{J}|$ FLOPs. The gradient calculation in (7), being the most computationally intensive step, demands $10|\mathcal{J}|$ FLOPs, and updating the position estimation takes 4 FLOPs. In total, each iteration requires $18|\mathcal{J}| + 10$ FLOPs. For large T values, where the final cost calculation and the threshold comparison are negligible, the computational complexity of the GD-based solver is estimated as $\mathcal{C}_{\text{GD}} \approx T(18|\mathcal{J}| + 10)$ FLOPs.

V. NUMERICAL RESULTS

A. Evaluation Assumptions and Parametrization

We consider a 100 m^2 square evaluation region containing $I = 9$ randomly distributed antenna points that emulate a cell-free (CF) network topology. The APs are randomly deployed within the region while ensuring a minimum separation distance between them to avoid unrealistic clustering. Within this configuration, both the reference AP and the indices of remaining APs are randomly designated. The uplink pilot design adheres to the 5G-NR sounding reference signal (SRS) framework as specified in [26], operating at a carrier frequency of 2300 MHz (5G NR band n40) with a subcarrier spacing of 15 kHz. A total of 4 resource blocks are allocated for the pilot transmission, combined with a comb factor of 4, yielding an uplink reference signal bandwidth of 180 kHz. A single reference symbol configuration [26] is employed, and the modulation scheme used is BPSK. The channel is modeled using the free space path-loss model. Additional simulation parameters include a noise power spectral density (PSD) of -174 dBm/Hz , a receiver noise figure of 13 dB, and uplink transmit power levels of $\{-20, -10, 0\} \text{ dBm}$.

The considered failure probabilities are $p_f \in \{0, 10^{-3}, 10^{-2}\}$. We select the set of AP indices for which differential ambiguities will be estimated as $\mathcal{J} = \{1, \dots, 8\}$, such that the MLP-based model estimates all failure-independent differential ambiguities $\Delta\bar{z} = [\Delta\bar{z}_1, \dots, \Delta\bar{z}_8]^\top$. With the selected set of APs, the total number of possible output classes for the failure-independent differential ambiguities $[\Delta\bar{z}_1, \dots, \Delta\bar{z}_8]^\top$ is calculated as $Q = 334$.

From a geometric perspective, estimating any two differential ambiguities yields two differential distance estimates which define two hyperbolas. The intersection of these hyperbolas provides already a unique positioning solution for the UE under ideal conditions. However, by estimating a larger set of differential ambiguities, the model benefits from additional geometric constraints, which enhance localization accuracy and improve robustness against noise and potential incorrect estimation of the differential ambiguities. The selection of the AP indices whose ambiguities are estimated and the analysis of the performance-complexity trade-off as a function of $|\mathcal{J}|$ are left as important directions for future work.

The layer parameter of the MLP-based differential ambiguity estimator is set as $D = 128$. For evaluation purposes, separate NN estimators are trained for each combination of transmission power level and failure probability p_f using a supervised learning methodology. Each configuration utilizes 700×10^3 training samples and 150×10^3 validation samples, with randomly selected UE positions for each sample instance. For each failure probability p_f , both the training and validation datasets are generated to reflect the corresponding failure conditions, ensuring that the model learns under the intended operating scenarios. The training process employs a batch size of 500 samples over 500 epochs. Network optimization is achieved through the Adam optimizer, configured with a learning rate of 10^{-3} , while L2 regularization with a coefficient of 10^{-5} , and a dropout rate of 0.1 is applied during training to prevent overfitting. The GD-based solver is configured to run for $T = 500$ iterations, with a learning rate of $\alpha = 0.08$.

B. Differential Ambiguity Estimation Results

The performance of the MLP-based differential ambiguity estimator is measured using the overall accuracy metric, defined as

$$A_o = \frac{1}{S} \sum_{s=1}^S \mathbb{I}(\Delta\hat{z}^s = \Delta\bar{z}^s) \times 100\%, \quad (8)$$

where $\mathbb{I}(\cdot)$ is the indicator function, which equals 1 when its argument is true and 0 otherwise, and $\Delta\hat{z}^s$ and $\Delta\bar{z}^s$ are the estimated and true failure-independent differential ambiguity vectors for the test sample s , respectively. The obtained overall accuracy results for the trained models are summarized in Table I, based on a test set containing $S = 100 \times 10^3$ samples. Evaluations are conducted across various uplink transmit power levels and AP failure probabilities. For each value of the failure probability p_f , the test dataset is generated following the same procedure as for the training and validation datasets, ensuring that the failure patterns reflect the corresponding operating conditions.

As anticipated, A_o improves consistently with increasing transmit power, reflecting the enhanced impact of signal quality on the estimator. With 9 distributed APs in the system, the probability of experiencing no failures is approximately 0.991 for $p_f = 10^{-3}$. This indicates that the vast majority

TABLE I
ACCURACY OF DIFFERENTIAL AMBIGUITY ESTIMATION

Failure Probability	Transmit Power [dBm]		
	-20	-10	0
$p_f = 0$	98.69%	99.52%	99.80%
$p_f = 10^{-3}$	98.15%	99.13%	99.38%
$p_f = 10^{-2}$	96.93%	97.79%	98.11%

TABLE II
95TH PERCENTILE POSITIONING ERRORS OF DIFFERENT MODELS

Approach	Transmit Power [dBm]		
	-20	-10	0
Proposed approach, $p_f = 0$	1.35cm	0.42cm	0.14cm
Proposed approach, $p_f = 10^{-3}$	1.43cm	0.45cm	0.15cm
Proposed approach, $p_f = 10^{-2}$	1.88cm	0.65cm	0.21cm
MLP-based approach in [10], $p_f = 0$	4.54cm	4.05cm	4.01cm
CNN-based approach in [10], $p_f = 0$	3.16cm	2.83cm	2.08cm

of test samples operate under failure-free conditions, yet a slight performance degradation is observed compared to the ideal case of $p_f = 0$. This phenomenon occurs because the model encounters a small portion of samples with AP failures at $p_f = 10^{-3}$, which may not provide sufficient training examples for the estimator to effectively learn robust prediction strategies under failure conditions. On the other hand, for $p_f = 10^{-2}$, approximately 8.65% of the training samples experience at least one AP failure. With this increased exposure to failure scenarios, the model learns to better handle degraded conditions, though a performance reduction compared to the failure-free case is still observed due to the inherent complexity of estimation under AP failures. These results validate the robustness of the proposed ambiguity estimation model under varying AP failure probabilities.

C. Positioning Results

To benchmark the positioning performance, we compare against the positioning approaches presented in [10], which assume ideal AP operating conditions with $p_f = 0$. Table II presents the 95th percentile positioning errors across different uplink transmit power levels and failure probabilities. The results demonstrate that the proposed approach achieves superior performance even under AP failure scenarios. This performance advantage is attributed to the high accuracy of the MLP-based ambiguity estimator, as evidenced in Table I.

The empirical cumulative distribution function (ECDF) curves for a transmit power of 0 dBm are shown in Fig. 4. The proposed approach demonstrates superior accuracy in the sub-centimeter regime. The performance degradation under AP failures can be explained through (6). Although the ambiguities are estimated with high accuracy as shown in Table I, AP failures still impact UE position estimation due to the addition of the estimated ambiguities with differential phase measurements, which are also affected by AP failures (2). Nevertheless, these results confirm the reliability and precision of the proposed positioning approach under varying AP failure conditions.

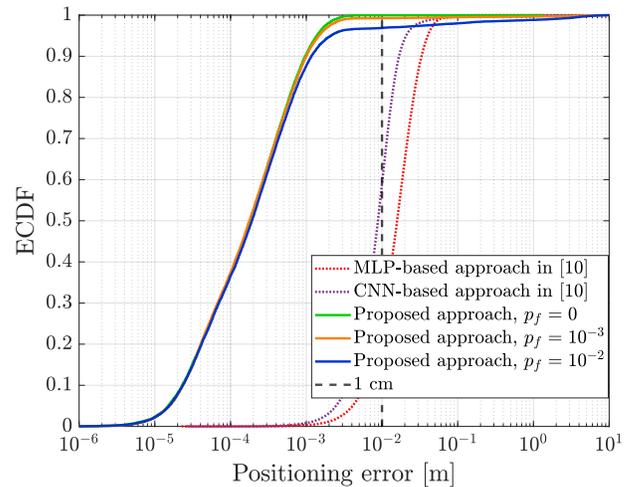


Fig. 4. ECDF of the proposed approach and NN approaches in previous work at a transmit power of 0 dBm. The previous work benchmark performance assumes failure-free data ($p_f = 0$).

D. Failure Detection Results

In order to evaluate the failure detection capabilities of the proposed models, four distinct test sets were constructed, each consisting of $S = 100 \times 10^3$ samples. The first test set, referred to as the No Failure dataset, contains samples in which no APs are malfunctioning. In contrast, the remaining three datasets—1 Failure, 2 Failures, and 3 Failures—simulate the scenarios in which one, two, or three APs, respectively, are always failing. The indices of the failing APs in these test sets are selected randomly for each test sample to ensure generality and prevent bias toward any specific APs. The failure detection performance of the models under these varying failure conditions is assessed by calculating the ratio of test samples that successfully pass the threshold test, i.e., $E_T \leq \tau$, with the detection threshold set here to $\tau = 10^{-4}$.

The failure detection results are presented in Table III for models trained with varying failure probabilities and transmit power levels. The model trained with the failure probability of $p = 0$, which is trained exclusively on No Failure samples, demonstrates the highest pass rate on the No Failure test set. It consistently outperforms models trained with $p = 10^{-3}$ and $p = 10^{-2}$. On the other hand, in the presence of failures in the test data, a different trend emerges. As the value of p increases, indicating more exposure to failure cases during training, the models demonstrate worse detection capability by allowing a larger portion of the samples to pass the threshold test. Notably, for all three model configurations, the percentage of samples that pass the threshold in the No Failure test set exceeds 99%, indicating strong agreement with non-faulty data. In contrast, for the 3 Failures test set, the pass ratio drops below 1% across all models. This stark contrast in detection rates between non-failure and multiple-failure scenarios highlights the models' ability to distinguish between nominal and anomalous conditions. In general, the high failure detection reliability contributes to increased positioning integrity, particularly when it comes to the ECDF tails visible

TABLE III
RATIO OF THE TEST SAMPLES THAT PASSES THE THRESHOLD TEST,
 $\tau = 10^{-4}$

Testset	p_f in the training set	Transmit Power [dBm]		
		-20	-10	0
No failure	0	99.70%	99.71%	99.83%
	10^{-3}	99.49%	99.62%	99.75%
	10^{-2}	99.46%	99.54%	99.68%
1 failure	0	16.05%	17.01%	17.19%
	10^{-3}	16.97%	17.29%	17.90%
	10^{-2}	17.08%	18.53%	18.97%
2 failures	0	2.11%	2.48%	2.69%
	10^{-3}	2.14%	2.60%	2.88%
	10^{-2}	2.26%	2.82%	2.93%
3 failures	0	0.11%	0.15%	0.47%
	10^{-3}	0.14%	0.36%	0.53%
	10^{-2}	0.42%	0.50%	0.65%

in Fig. 4.

E. Inference Complexity Comparison

Based on the inference complexity derivations in Section IV, the NN-based differential ambiguity estimator has a complexity of $\mathcal{C}_{\text{NN}} \approx 0.877 \times 10^6$ FLOPs, while the GD solver requires $\mathcal{C}_{\text{GD}} \approx 0.077 \times 10^6$ FLOPs. The combined approach yields a total computational complexity of $\mathcal{C}_{\text{T}} \approx 0.954 \times 10^6$ FLOPs, achieving complexity reductions of approximately 30.7% and 16.9% relative to MLP-based positioning (1.376×10^6 FLOPs) and convolutional neural network (CNN)-based positioning (1.148×10^6 FLOPs) methods reported in [10], respectively.

VI. CONCLUSION

This work proposed methods to improve the accuracy of carrier phase-only UE positioning in distributed MIMO or cell-free systems beyond the existing state-of-the-art, while also considering and involving practical antenna element failures by leveraging a learning-based NN approach. The proposed differential ambiguity estimator achieves high accuracy across varying uplink transmit powers and failure probabilities, demonstrating robustness under practical system impairments. Positioning performance remains highly reliable, with 95th percentile errors consistently below 2 cm—even under moderate antenna failure rates—validating the method’s suitability for stringent centimeter-level positioning requirements. Furthermore, the failure detection capability of the models shows strong generalization: training with failure scenarios improves robustness, enabling effective identification of faulty antenna conditions without compromising performance in fault-free cases. Overall, the results confirm that deep learning-driven phase-only positioning offers a promising solution that is resilient to antenna failures, ensuring precise and dependable localization in next-generation mobile networks. Future work will focus on investigating the impact of non-line-of-sight (NLoS) and multipath effects on the proposed positioning framework. Additionally, we aim to explore the influence of residual phase-calibration errors at the network side.

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