

DNN-Based Phase Prediction for Distributed Multi-RIS Systems under Co-Channel Interference

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ABSTRACT

This paper investigates learning-assisted 2-bit phase control for distributed reconfigurable intelligent surfaces (RISs) under co-channel interference. Exhaustive RIS activation (ERA) uses all surfaces, whereas opportunistic RIS activation (ORA) selects the surface with the largest instantaneous signal-to-interference-plus-noise ratio. A deep neural network (DNN) uses channel-derived features to approximate an offline discrete coordinate-ascent (DCA) teacher maximizing the high-SNR signal-to-interference ratio (SIR). ERA predicts residual corrections to quantized phase alignment (QPA), using class-balanced cross-entropy, a utility-aware SIR-gap loss, and post-warm-up checkpoint selection. ORA predicts absolute phase states. Fixed phases, QPA, DCA, and continuous-phase alignment provide common benchmarks. On an independent test set, mean DCA-DNN SIR gaps are 0.0435 dB for ERA and 0.0843 dB for ORA. At 25 dBm, corresponding ergodic-capacity gaps are 0.0040 and 0.0063 b/s/Hz. High-SNR analysis establishes nonzero outage floors and finite capacity ceilings when desired and interfering transmit powers scale together. The DNN provides an iteration-free surrogate retaining most teacher utility, while QPA remains competitive and the channel-state-information requirement is retained.

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1. INTRODUCTION

Reconfigurable intelligent surfaces (RISs) provide a programmable means of shaping radio propagation by adjusting the responses of large arrays of nearly passive reflecting elements [1–4]. By avoiding a dedicated radio-frequency chain at each reflecting element, RIS-assisted transmission is attractive for coverage extension, blockage mitigation, and energy-aware wireless design. When several RISs are geographically distributed, additional macro-diversity and path-selection opportunities become available. In particular, distributed multi-RIS systems can operate with exhaustive RIS activation (ERA), where all RISs participate, or opportunistic RIS activation (ORA), where only the most favorable RIS is selected [5].

A major practical difficulty is that an RIS modifies both useful and interfering propagation paths. In a multi-cell setting with frequency reuse, a phase vector that strengthens the desired cascaded path may simultaneously enhance co-channel interference (CCI). The resulting design objective is therefore interference coupled rather than a simple desired-signal phase-alignment problem [6, 7]. This issue becomes more challenging as the number of RIS elements grows because phase optimization is high dimensional and the available phase states are typically discrete rather than continuous.

Accurate channel state information (CSI) is another central concern. Since a passive RIS does not con-

ventionally contain active radio-frequency chains, estimation of the cascaded base-station–RIS–user channels can require substantial training and signaling overhead [8]. Learning-assisted phase control does not automatically eliminate that burden. A neural model whose input consists of channel coefficients or channel-derived features still requires those observations. Accordingly, the present paper does *not* claim CSI-free operation. Its purpose is narrower and more defensible: after the required channel-related observations have been obtained, a trained DNN replaces repeated online combinatorial/iterative phase optimization with a single forward inference operation.

Low-resolution phase shifters provide a second motivation. Practical RIS implementations often employ a small number of phase states to reduce hardware cost and control overhead. Early learning-based RIS studies demonstrated that deep learning and deep reinforcement learning can approximate phase-configuration policies with low online latency [9–12]. More recent work has moved beyond generic fully connected networks. For example, graph neural networks (GNNs) have been used to exploit distributed wireless topology in multi-RIS optimization [13]; lightweight unsupervised networks have been developed to avoid externally generated labels [14, 15]; heterogeneous graph transformers have been considered for RIS-aided THz resource and phase design [16]; self-supervised reinforcement learning has been proposed for RIS-assisted energy-efficiency optimization [17]; and complex-valued geometry-aware learning has been used to preserve phase-domain structure [19]. Low-bit learning has also advanced through end-to-end discrete phase techniques such as Gumbel-Softmax-based 2-bit control [18] and quantization-aware learning for practical STAR-RIS phase constraints [20].

These developments show that predicting a quantized RIS phase with a generic DNN is not, by itself, a sufficient novelty claim. The remaining gap addressed here is instead the *joint system-level evaluation* of low-complexity 2-bit phase prediction for distributed multi-RIS operation under explicit CCI, including both ERA and ORA, fair discrete-phase baselines, and a mathematical explanation of the interference-limited high-power behavior. The proposed predictors are deliberately implemented as fixed-topology fully connected networks so that their online cost can be stated transparently and compared with optimization-based alternatives.

1.1. Main Contributions

The main contributions of this work are summarized as follows.

- We formulate ERA and ORA for a distributed multi-RIS downlink in which the same RIS phase configuration shapes the desired signal and two co-channel interfering signals. The 2-bit phase-control objective is therefore interference-aware and is evaluated through the instantaneous SINR/SIR rather than desired-signal power alone.
- We construct an offline DCA teacher initialized by QPA and optimized with a high-SNR SIR objective. This gives a strong, reproducible 2-bit local-search benchmark while avoiding the exponential cost of exhaustive phase enumeration.
- For ERA, we introduce a QPA-residual learning formulation, $\Delta q_k = (q_k^{\text{DCA}} - q_k^{\text{QPA}}) \bmod 4$, so that the DNN learns only the interference-aware corrections applied by DCA. To address the strongly imbalanced residual labels, we use class-balanced cross-entropy together with a utility-aware SIR-gap loss and select the post-warm-up checkpoint using the hard validation DCA–DNN SIR gap. ORA retains absolute 2-bit phase prediction with the same utility-aware training principle.
- We provide a leakage-free 70%/15%/15% realization-level split and report learning fidelity in terms of both phase-state statistics and system utility. On the independent comparison set, the mean DCA–DNN SIR gaps are 0.0435 dB for ERA and 0.0843 dB for ORA; for ERA, the DNN changes 6.54% of QPA phase states, compared with 10.00% for the DCA teacher, and matches the DCA phase state on 85.22% of coordinates.
- We compare the proposed DNN with fixed phases, QPA, DCA, and CPA on identical channel realizations and derive the high-SNR ERA/ORA limits. The analysis shows that common scaling of desired and interfering powers produces a nonzero outage floor and a finite capacity ceiling, while the numerical results quantify the remaining DNN–DCA gap without claiming that the DNN universally outperforms the strong QPA heuristic.

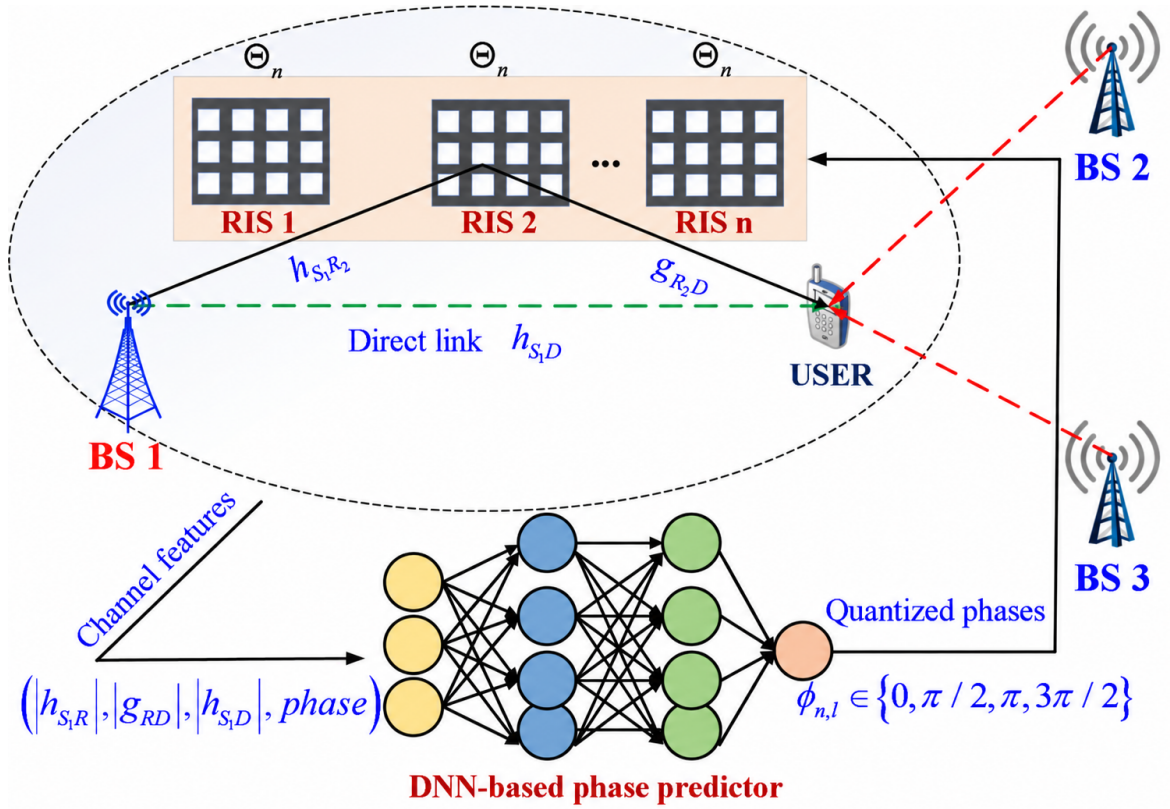


Figure 1. Distributed multi-RIS multi-cell downlink under CCI. BS 1 is the desired transmitter, BS 2 and BS 3 are co-channel interferers, and the distributed RISs assist the BS–user links.

The remainder of the paper follows the IJEET-style organization. Section II describes the research method, including the signal model, phase-design problem, learning procedure, benchmarks, asymptotic analysis, and complexity. Section III presents the results and discussion. Section IV concludes the paper.

2. RESEARCH METHOD

2.1. Network and Channel Model

Fig. 1 illustrates a downlink composed of three single-antenna base stations (BSs), one single-antenna destination D , and N distributed RISs. BS 1 is the desired transmitter, whereas BS 2 and BS 3 reuse the same time–frequency resource and act as co-channel interferers. RIS n contains L passive reflecting elements.

The direct link from BS i to D is denoted by $h_{S_i,D} \in \mathbb{C}$. The BS- i –RIS- n channel and the RIS- n –destination channel are denoted by $\mathbf{h}_{S_i,R_n} \in \mathbb{C}^{L \times 1}$ and $\mathbf{g}_{R_n,D} \in \mathbb{C}^{L \times 1}$, respectively. The channel envelopes follow independent, not necessarily identically distributed Nakagami- m laws. For a generic coefficient z , the envelope $r = |z|$ has density

$$f_{|z|}(r) = \frac{2m^m}{\Gamma(m)\Omega^m} r^{2m-1} \exp\left(-\frac{mr^2}{\Omega}\right), \quad r \geq 0, \quad (1)$$

where $m \geq 1/2$ is the fading-shape parameter and $\Omega = \mathbb{E}[|z|^2]$ is the average power. Different links may use different Ω values to represent unequal large-scale attenuation, although the numerical setting in Table 3 uses a common shape parameter.

2.2. RIS Reflection Model

The reflection matrix of RIS n is

$$\mathbf{\Theta}_n = \kappa \text{diag}\left(e^{j\phi_{n,1}}, \dots, e^{j\phi_{n,L}}\right), \quad (2)$$

where $0 < \kappa \leq 1$ is the reflection amplitude. For a B -bit phase shifter, the feasible codebook is

$$\mathcal{Q}_B = \left\{ \frac{2\pi q}{2^B} : q = 0, 1, \dots, 2^B - 1 \right\}. \quad (3)$$

The study focuses on $B = 2$, so

$$\mathcal{Q} \equiv \mathcal{Q}_2 = \left\{ 0, \frac{\pi}{2}, \pi, \frac{3\pi}{2} \right\}. \quad (4)$$

2.3. ERA: All RISs Active

When all RISs are active, the equivalent desired channel is

$$H_1^{\text{ERA}} = h_{S_1 D} + \sum_{n=1}^N \mathbf{g}_{R_n D}^T \mathbf{\Theta}_n \mathbf{h}_{S_1 R_n}, \quad (5)$$

and the equivalent interference channel from BS $i \in \{2, 3\}$ is

$$H_i^{\text{ERA}} = h_{S_i D} + \sum_{n=1}^N \mathbf{g}_{R_n D}^T \mathbf{\Theta}_n \mathbf{h}_{S_i R_n}. \quad (6)$$

With transmit powers P_1, P_2, P_3 and receiver-noise power σ^2 , the ERA SINR is

$$\gamma_{\text{ERA}} = \frac{P_1 |H_1^{\text{ERA}}|^2}{\sum_{i=2}^3 P_i |H_i^{\text{ERA}}|^2 + \sigma^2}. \quad (7)$$

The 2-bit ERA phase-design problem is

$$\begin{aligned} & \underset{\{\phi_{n,\ell}\}}{\text{maximize}} && \gamma_{\text{ERA}} \\ & \text{subject to} && \phi_{n,\ell} \in \mathcal{Q}, \\ & && n = 1, \dots, N, \ell = 1, \dots, L. \end{aligned} \quad (8)$$

The feasible set contains 4^{NL} configurations, which makes exhaustive search impractical even for moderate N and L .

2.4. ORA: One RIS Active

For candidate RIS n , define

$$H_{1,n} = h_{S_1 D} + \mathbf{g}_{R_n D}^T \mathbf{\Theta}_n \mathbf{h}_{S_1 R_n}, \quad (9)$$

$$H_{i,n} = h_{S_i D} + \mathbf{g}_{R_n D}^T \mathbf{\Theta}_n \mathbf{h}_{S_i R_n}, \quad i \in \{2, 3\}. \quad (10)$$

The candidate SINR is

$$\gamma_n = \frac{P_1 |H_{1,n}|^2}{\sum_{i=2}^3 P_i |H_{i,n}|^2 + \sigma^2}. \quad (11)$$

For each candidate RIS, its quantized phase vector is optimized/predicted and the selected index is

$$n^* = \arg \max_{n \in \{1, \dots, N\}} \gamma_n. \quad (12)$$

Thus

$$\gamma_{\text{ORA}} = \gamma_{n^*}. \quad (13)$$

Because each ORA candidate contains only L controllable elements, exhaustive per-candidate search would still require $N4^L$ phase evaluations and remains infeasible for $L = 64$.

2.5. Performance Metrics

For target spectral efficiency R b/s/Hz, the outage threshold is

$$\gamma_{\text{th}} = 2^R - 1. \quad (14)$$

The outage probability (OP) is

$$P_{\text{out}} = \Pr\{\gamma < \gamma_{\text{th}}\}, \quad (15)$$

and the ergodic capacity (EC) is

$$C = \mathbb{E}[\log_2(1 + \gamma)], \quad (16)$$

where γ is either γ_{ERA} or γ_{ORA} .

2.6. Interference-Aware Feature Construction

Because the phase configuration affects both the desired and interfering reflected links, an SINR-oriented predictor must represent the cascaded channels associated with all three BSs. Accordingly, the adopted feature construction explicitly includes the desired and two interfering cascaded channels.

For BS i and RIS n , define the element-wise cascaded channel

$$\mathbf{c}_{i,n} = \mathbf{g}_{R_n D} \odot \mathbf{h}_{S_i R_n} \in \mathbb{C}^{L \times 1}, \quad i \in \{1, 2, 3\}, \quad (17)$$

where $\odot$ denotes the Hadamard product. A local real-valued feature vector for RIS n is

$$\mathbf{x}_n = [\Re\{\mathbf{c}_{1,n}\}^T, \Im\{\mathbf{c}_{1,n}\}^T, \Re\{\mathbf{c}_{2,n}\}^T, \Im\{\mathbf{c}_{2,n}\}^T, \Re\{\mathbf{c}_{3,n}\}^T, \Im\{\mathbf{c}_{3,n}\}^T]^T, \quad (18)$$

so that $\mathbf{x}_n \in \mathbb{R}^{6L}$. The direct-link feature vector is

$$\mathbf{d} = [\Re\{h_{S_1 D}\}, \Im\{h_{S_1 D}\}, \Re\{h_{S_2 D}\}, \Im\{h_{S_2 D}\}, \Re\{h_{S_3 D}\}, \Im\{h_{S_3 D}\}]^T, \quad (19)$$

where $\mathbf{d} \in \mathbb{R}^6$. Before training, each real-valued feature is standardized using the mean and standard deviation computed from the training set only.

For ERA, the DNN input is the global vector

$$\mathbf{x}_{\text{ERA}} = [\mathbf{x}_1^T, \dots, \mathbf{x}_N^T, \mathbf{d}^T]^T \in \mathbb{R}^{6NL+6}. \quad (20)$$

For $N = 3$ and $L = 64$, its dimension is $6NL + 6 = 1158$. For ORA, the same local predictor is applied to each candidate RIS using

$$\mathbf{x}_{\text{ORA},n} = [\mathbf{x}_n^T, \mathbf{d}^T]^T \in \mathbb{R}^{6L+6}, \quad (21)$$

which has dimension 390 for $L = 64$.

This formulation should not be interpreted as reducing the cost of estimating the underlying cascaded channels. Rather, it makes the phase-control stage interference aware while avoiding the need to solve (8) or its ORA counterpart iteratively during online operation.

2.7. Offline Teacher-Label Generation

Supervised learning requires target phase labels. Nearest-neighbor quantized phase alignment (QPA) provides a low-complexity 2-bit initializer, but it aligns only the desired component and does not explicitly optimize the CCI-coupled utility. Therefore, interference-aware labels are generated offline by discrete coordinate ascent (DCA).

Since all three BS powers are swept together, $P_1 = P_2 = P_3 = P_s$, the high-SNR phase objective is independent of the common power scale. For ERA, define

$$J_{\text{ERA}}(\phi) = \frac{|H_1^{\text{ERA}}|^2}{|H_2^{\text{ERA}}|^2 + |H_3^{\text{ERA}}|^2 + \varepsilon_0}, \quad (22)$$

where $\varepsilon_0 > 0$ is a small numerical regularizer. The initial 2-bit vector is the QPA solution in (35). During DCA sweep t , one coordinate is updated while all remaining coordinates are fixed:

$$\phi_k^{(t+1)} = \arg \max_{\phi \in \mathcal{Q}} J_{\text{ERA}}(\phi_1, \dots, \phi_{k-1}, \phi, \phi_{k+1}, \dots), \quad (23)$$

where k indexes the NL RIS elements. The implementation uses at most $I_{\text{max}} = 3$ sweeps and stops earlier when the relative objective improvement is below $\epsilon = 10^{-4}$. Equivalent channels are updated incrementally, so each candidate phase test modifies only the contribution of the current coordinate. Because every accepted coordinate update is non-decreasing and the feasible set is finite, DCA terminates at a coordinate-wise local optimum.

For ORA, the same procedure is applied independently to each candidate RIS using

$$J_n(\phi_n) = \frac{|H_{1,n}|^2}{|H_{2,n}|^2 + |H_{3,n}|^2 + \varepsilon_0}. \quad (24)$$

The optimized candidate phase vectors become the supervised labels, while the final RIS index is selected from the instantaneous finite-SNR SINRs according to (12). Thus, the teacher labels are interference-aware local optima rather than globally optimal ground truth.

For M channel realizations, the ERA labeling cost is on the order of

$$\mathcal{O}(MI_{\text{max}}QNL), \quad (25)$$

with $Q = |\mathcal{Q}| = 4$. ORA requires the same order per candidate RIS. This cost is incurred offline only; the trained DNN subsequently replaces repeated coordinate searches by a forward pass.

2.8. DNN Architecture and Training

The learning implementation uses fully connected predictors with interference-aware channel-derived inputs. The ERA predictor consumes the global feature vector in (20). For $N = 3$ and $L = 64$, the implemented architecture is

$$1158 \rightarrow 1024 \rightarrow 512 \rightarrow 256 \rightarrow 768, \quad (26)$$

where ReLU activations are used in the hidden layers and $768 = 4NL$ output logits are reshaped to $NL \times 4$. The ERA network contains 2,040,320 trainable parameters. The ORA predictor consumes (21), shares one set of weights across the N candidate RISs, and uses

$$390 \rightarrow 512 \rightarrow 256 \rightarrow 128 \rightarrow 256, \quad (27)$$

where $256 = 4L$. The ORA network contains 397,440 trainable parameters.

For ERA, directly learning the absolute DCA labels is unnecessarily difficult because DCA is initialized from QPA and only a minority of coordinates are changed. Let q_k^{QPA} and q_k^{DCA} denote the 2-bit state indices of coordinate k . The ERA target is therefore the residual class

$$\Delta q_k = (q_k^{\text{DCA}} - q_k^{\text{QPA}}) \bmod 4, \quad (28)$$

and the reconstructed DNN phase index is

$$\hat{q}_k^{\text{DNN}} = (q_k^{\text{QPA}} + \hat{\Delta q}_k) \bmod 4. \quad (29)$$

This formulation provides a physically meaningful fallback: predicting $\hat{\Delta q}_k = 0$ leaves the corresponding QPA state unchanged. In the 10^4 -realization training dataset, the four ERA residual classes occur with fractions approximately (0.9002, 0.0484, 0.0034, 0.0481), so an unweighted classifier is strongly biased toward the zero-correction class.

To reduce this imbalance, the ERA cross-entropy uses weights computed from the training split only. If p_q is the empirical frequency of residual class q , the unnormalized weight is $p_q^{-\alpha}$ with $\alpha = 0.5$; the four weights are then normalized to have unit mean and clipped at 4 if necessary. The resulting weights are

$$\mathbf{w} = [0.1547, 0.6664, 2.5109, 0.6680]. \quad (30)$$

The class-balanced loss is

$$\mathcal{L}_{\text{CBCE}} = -\frac{1}{K} \sum_{k=1}^K w_{\Delta q_k} \log \hat{p}_{k, \Delta q_k}, \quad (31)$$

with $K = NL$ for ERA. ORA uses the absolute DCA phase states as four-class targets and standard, un-weighted element-wise cross-entropy with $K = L$ for each candidate RIS.

Phase-label agreement alone is not a sufficient training criterion because distinct quantized phase vectors can have nearly identical SIR. We therefore include a utility-aware term based on the same physical objective as the DCA teacher. For a training sample, let J_{DCA} be the high-SNR SIR obtained by the absolute teacher phase vector and let J_{DNN} be the SIR produced by the hard DNN decision. The positive utility gap is

$$g = \left[10 \log_{10} \left(\frac{J_{\text{DCA}}}{J_{\text{DNN}}} \right) \right]_+, \quad (32)$$

where $[x]_+ = \max(x, 0)$. A straight-through softmax estimator is used so that hard 2-bit decisions are evaluated in the forward pass while gradients remain available during backpropagation. The utility term is a smooth- L_1 penalty on $g/3$, denoted by $\mathcal{L}_{\text{U}}$, and the training objective is

$$\mathcal{L} = \mathcal{L}_{\text{cls}} + \lambda_{\text{U}}(e) \mathcal{L}_{\text{U}}, \quad (33)$$

where $\mathcal{L}_{\text{cls}} = \mathcal{L}_{\text{CBCE}}$ for ERA and the ordinary cross-entropy for ORA. The utility weight is zero for the first eight warm-up epochs and then increases linearly to $\lambda_{\text{U}} = 0.35$ over the following eight epochs. The straight-through temperature is geometrically annealed from 1.0 to 0.35 over at most 100 epochs.

Training uses AdamW with initial learning rate 7×10^{-4} , weight decay 10^{-5} , gradient-norm clipping at 5, and mini-batches of 128 for ERA and 256 for ORA. A realization-level 70%/15%/15% split is used for training, validation, and testing. The $NM = 30,000$ ORA candidate samples inherit the split of their parent channel realization so that candidates from the same realization cannot leak across subsets. Feature standardization is fitted on the training split only. The random seed is 42 for data generation/training, while the independent performance simulation uses seed 2026.

Checkpoint selection is deliberately different for the two predictors. For ERA, no checkpoint is eligible during the eight-epoch cross-entropy warm-up; afterward, the checkpoint minimizing the mean positive hard-validation DCA–DNN SIR gap is retained, with balanced cross-entropy used only as a tie-breaker. This prevents an early majority-class solution from being selected before utility-aware learning is active. ORA selects the checkpoint by validation combined loss. The selected checkpoints occur at epoch 93 for ERA and epoch 33 for ORA, with measured CPU training times of 141.45 s and 41.38 s, respectively. The training environment used PyTorch 2.9.1 (CPU) and NumPy 2.3.5.

2.9. Comparison Methods

To avoid an artificially weak comparison, five phase-control strategies are considered.

- 1) **Fixed phase:** all RIS elements use $\phi_{n,\ell} = 0$. This is retained only as a non-adaptive reference.
- 2) **Continuous phase alignment (CPA):** ignoring CCI during the initial alignment step, the desired reflected component is aligned with the desired direct link. When $h_{S_1 D} \neq 0$,

$$\phi_{n,\ell}^{\text{CPA}} = \arg(h_{S_1 D}) - \arg(c_{1,n,\ell}) \pmod{2\pi}. \quad (34)$$

If the direct path is negligible, a common reference phase is used. CPA is a continuous-phase reference, not a guaranteed global optimum of the CCI-coupled SINR problem.

- 3) **Quantized phase alignment (QPA):** each CPA phase is projected to its nearest 2-bit state,

$$\phi_{n,\ell}^{\text{QPA}} = \arg \min_{\phi \in \mathcal{Q}} d_c(\phi, \phi_{n,\ell}^{\text{CPA}}), \quad (35)$$

where $d_c(a, b) = |\angle e^{j(a-b)}|$ is circular distance. QPA is both a strong low-cost baseline and the initializer for DCA.

- 4) **DCA:** the interference-aware coordinate optimizer in (23) and (24) is used as the strongest discrete benchmark considered here and as the offline teacher. DCA returns a coordinate-wise local optimum rather than a globally optimal phase vector.

Table 1. DNN and training configuration.

Item	Value
ERA architecture	1158–1024–512–256–768
ORA architecture	390–512–256–128–256
Trainable parameters	2,040,320 (ERA); 397,440 (ORA)
Hidden activation	ReLU
Output	4 logits per RIS element
ERA target	QPA residual Δq
ORA target	Absolute DCA phase state
ERA class balancing	$p_q^{-1/2}$, normalized; max weight 4
Utility weight	$0 \rightarrow 0.35$ after 8-epoch warm-up
Temperature	$1.0 \rightarrow 0.35$
Optimizer	AdamW
Initial learning rate	7×10^{-4}
Weight decay	10^{-5}
Mini-batch size	128 (ERA), 256 (ORA)
Maximum epochs	100
Early-stopping patience	15 eligible epochs
Data split	70% / 15% / 15% by realization
ERA training realizations	$M = 10,000$
ORA candidate samples	$NM = 30,000$
DCA maximum sweeps	$I_{\max} = 3$
DCA tolerance	$\epsilon = 10^{-4}$
Best epoch	93 (ERA), 33 (ORA)
Training time	141.45 s (ERA), 41.38 s (ORA)
Training software	PyTorch 2.9.1 CPU; NumPy 2.3.5
Random seed	42 (train), 2026 (independent test)

5) Proposed DNN: for ERA, the network predicts QPA-relative residual classes according to (28)–(29); for ORA, it predicts absolute 2-bit phase states. The purpose of the DNN is to reproduce most of the interference-aware DCA utility using a fixed forward mapping, not to guarantee improvement over QPA in every finite-SNR operating point.

The most informative practical comparison is therefore *DNN versus QPA versus DCA*. Fixed phase is a non-adaptive reference, whereas CPA shows the behavior of continuous desired-link alignment but is not an SINR-optimal upper bound under CCI.

2.10. High-SNR Interference-Limited Analysis

To characterize the interference-limited behavior observed at high transmit powers, the corresponding high-SNR expressions are derived next.

Let all three BS powers scale with a common parameter P :

$$P_i = \alpha_i P, \quad \alpha_i > 0, \quad i \in \{1, 2, 3\}. \quad (36)$$

Substituting (36) into (7) gives

$$\gamma_{\text{ERA}}(P) = \frac{\alpha_1 |H_1^{\text{ERA}}|^2}{\sum_{i=2}^3 \alpha_i |H_i^{\text{ERA}}|^2 + \sigma^2/P}. \quad (37)$$

Hence, provided the aggregate interference is nonzero,

$$\gamma_{\text{ERA}}^\infty = \lim_{P \rightarrow \infty} \gamma_{\text{ERA}}(P) = \frac{\alpha_1 |H_1^{\text{ERA}}|^2}{\sum_{i=2}^3 \alpha_i |H_i^{\text{ERA}}|^2}. \quad (38)$$

For the equal-power sweep used in this paper, $P_1 = P_2 = P_3 = P$, so

$$\gamma_{\text{ERA}}^{\infty} = \frac{|H_1^{\text{ERA}}|^2}{|H_2^{\text{ERA}}|^2 + |H_3^{\text{ERA}}|^2}. \quad (39)$$

Thus the SINR does not grow without bound when the desired and interfering powers increase together.

For ORA candidate n ,

$$\gamma_n^{\infty} = \frac{\alpha_1 |H_{1,n}|^2}{\sum_{i=2}^3 \alpha_i |H_{i,n}|^2}, \quad (40)$$

and the asymptotic selected SINR is

$$\gamma_{\text{ORA}}^{\infty} = \max_{n \in \{1, \dots, N\}} \gamma_n^{\infty}. \quad (41)$$

The corresponding outage floor is

$$P_{\text{out}}^{\infty} = \Pr\{\gamma^{\infty} < \gamma_{\text{th}}\}, \quad (42)$$

and the ergodic-capacity ceiling is

$$C^{\infty} = \mathbb{E}[\log_2(1 + \gamma^{\infty})]. \quad (43)$$

Equations (42)–(43) establish analytically that increasing all co-channel transmit powers together cannot remove the interference-limited floor. By contrast, if the desired power increased while the interferer powers remained fixed, the asymptotic behavior would be different; therefore, the saturation discussed here is specifically tied to the equal/common power-scaling model in Table 3.

2.11. Computational Complexity

For a fully connected DNN with dimensions $d_0, d_1, \dots, d_K$, the dominant forward-pass cost is

$$\mathcal{O}\left(\sum_{k=1}^K d_{k-1} d_k\right). \quad (44)$$

For the ERA architecture in (26), the dense matrix multiplications require approximately

$$1158(1024) + 1024(512) + 512(256) + 256(768) \approx 2.04 \times 10^6 \quad (45)$$

MAC-scale operations per realization. For one ORA candidate, (27) requires approximately

$$390(512) + 512(256) + 256(128) + 128(256) \approx 3.96 \times 10^5 \quad (46)$$

MAC-scale operations; evaluating all $N = 3$ candidates requires approximately 1.19×10^6 MAC-scale operations.

QPA requires phase computation and nearest-codebook projection and has approximately linear scaling with the number of RIS elements. DCA requires up to $I_{\text{max}} QNL$ coordinate candidate tests for ERA, or the corresponding per-candidate cost for ORA; the implementation updates equivalent channels incrementally, so each candidate test modifies only one coordinate contribution. Exhaustive discrete search remains exponential, requiring Q^{NL} objective evaluations for ERA or NQ^L for ORA. The DNN should therefore be interpreted as an iteration-free, fixed-complexity surrogate whose dense operations can be efficiently parallelized, rather than as an unconditional wall-clock speedup over every optimized DCA implementation. Table 2 summarizes these distinctions.

3. RESULTS AND DISCUSSION

3.1. Simulation Setting and Reproducibility

The simulations use a fixed geometry and fixed random seeds. BS 1, BS 2, BS 3, and the destination are located at $(0, 0)$, $(-44, 0)$, $(177, 0)$, and $(100, 0)$ m, respectively, while the three RISs are placed at $(20, 2)$, $(50, 6)$, and $(80, 4)$ m. Large-scale attenuation follows

$$\ell(d)_{\text{dB}} = -22.7 - 26 \log_{10}(f_c) - 36.7 \log_{10}(d), \quad (47)$$

Table 2. Online phase-control complexity comparison.

Method	Dominant online cost	Comment
Fixed phase	$\mathcal{O}(1)$	No adaptation
CPA	$\mathcal{O}(NL)$	Continuous desired-link alignment
QPA	approximately $\mathcal{O}(NL)$	2-bit projection heuristic
DCA	$\mathcal{O}(I_{\max} QNL)$ tests	Iterative local search
DNN	Eq. (44)	Fixed, parallelizable forward pass
Exhaustive	$\mathcal{O}(Q^{NL})$ (ERA)	Infeasible for $N = 3, L = 64$

Table 3. Communication and Monte Carlo parameters.

Parameter	Value
Number of RISs	$N = 3$
Elements per RIS	$L = 64$
RIS coordinates [m]	$(20, 2), (50, 6), (80, 4)$
BS/user coordinates [m]	$(0, 0), (-44, 0), (177, 0), (100, 0)$
Carrier frequency	$f_c = 3$ GHz
BS/RIS/user gains	5/5/0 dBi
Path-loss law	Eq. (47)
Reflection amplitude	$\kappa = 1$
Nakagami parameters	$m = 2, \Omega = 1$ before path loss
Noise power	$\sigma^2 = -90$ dBm
Target rate	$R = 1$ b/s/Hz
Transmit powers	$P_1 = P_2 = P_3 = P_s$
Power sweep	$P_s \in [-5, 25]$ dBm
Test realizations	$N_{\text{MC}} = 10^4$
Training realizations	$M = 10,000$
Phase resolution	2 bit, $Q = 4$

with $f_c = 3$ GHz. BS and RIS element gains are 5 dBi and the user gain is 0 dBi. Small-scale envelopes are Nakagami- m with fixed $m = 2$ and $\Omega = 1$ before large-scale scaling.

The desired and interfering BS powers are swept together, $P_1 = P_2 = P_3 = P_s$, from -5 to 25 dBm, while the receiver-noise power is fixed at -90 dBm. The target rate is $R = 1$ b/s/Hz. All five phase-control methods are evaluated on the same 10^4 independent Monte Carlo realizations with random seed 2026. The DNN training dataset is independent and contains 10^4 channel realizations generated with seed 42.

3.2. Fair Baseline Comparison

Five phase-control strategies are evaluated on exactly the same channel realizations: Fixed, QPA, the proposed DNN, DCA, and CPA. Fixed phases are retained only as a non-adaptive reference. QPA is a strong nearest-codebook phase-alignment heuristic, DCA is the interference-aware 2-bit teacher/local optimizer, and CPA is a continuous desired-link alignment reference rather than a guaranteed SINR upper bound.

3.3. ERA Performance

Figs. 2 and 3 show that all ERA schemes are strongly interference limited. Below approximately 10 dBm, the outage probabilities are close to one, and the performance differences among phase controllers are small. As P_s increases, phase adaptation becomes visible, but every curve eventually approaches a nonzero outage floor and a finite capacity ceiling because the desired and interfering powers scale together.

At $P_s = 20$ dBm, the proposed DNN achieves $P_{\text{out}} = 0.8880$ and $C = 0.515647$ b/s/Hz, compared with 0.8860 and 0.519082 b/s/Hz for DCA. Hence, the DNN-DCA outage gap is only 2.0×10^{-3} and the capacity gap is 3.435×10^{-3} b/s/Hz. At $P_s = 25$ dBm, the corresponding values are 0.8617 and 0.554677 b/s/Hz for the DNN versus 0.8600 and 0.558722 b/s/Hz for DCA. The capacity loss relative to DCA is therefore only 0.004045 b/s/Hz, approximately 0.72% of the DCA value. Relative to the non-adaptive fixed-phase case,

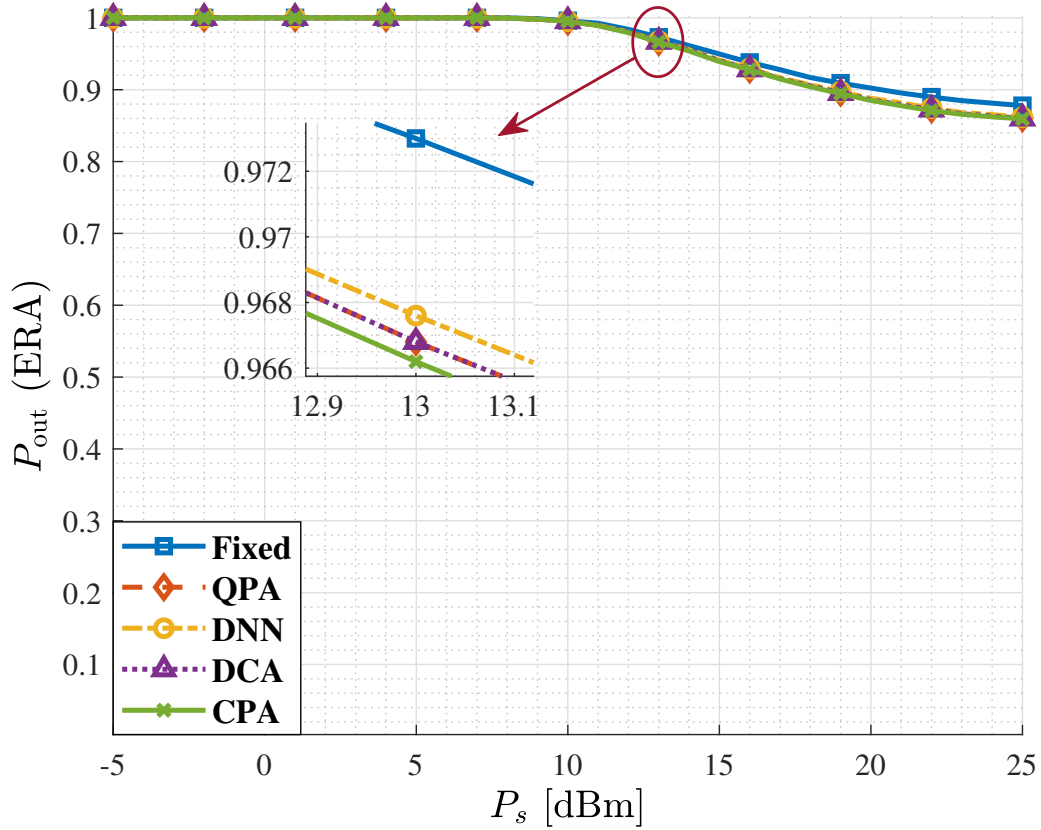


Figure 2. ERA outage probability versus P_s under CCI. Fixed, QPA, proposed DNN, DCA, and CPA are evaluated on identical channel realizations.

the DNN improves the 25-dBm capacity from 0.523106 to 0.554677 b/s/Hz, an increase of approximately 6.0%.

QPA remains a particularly strong baseline for ERA. At $P_s = 25$ dBm, QPA gives $P_{\text{out}} = 0.8608$ and $C = 0.557154$ b/s/Hz, which is slightly better than the DNN at this finite-SNR point. This result is important: the learning contribution should not be interpreted as universal superiority over QPA. Instead, the class-balanced residual DNN learns a sparse subset of interference-aware DCA corrections while preserving a small utility gap to the DCA teacher. The independent high-SNR test gives a mean DCA–DNN SIR gap of 0.0435 dB, a median gap of 0.0390 dB, and a 90th-percentile gap of 0.0709 dB; all tested realizations lie within 0.5 dB of DCA.

The high-SNR DNN floor/ceiling for ERA is

$$P_{\text{out,DNN}}^{\infty} = 0.8482, \quad C_{\text{DNN}}^{\infty} = 0.576005 \text{ b/s/Hz}, \quad (48)$$

whereas DCA gives 0.8456 and 0.580444 b/s/Hz, respectively. The close asymptotic values are consistent with the utility-based training objective.

3.4. ORA Performance

Figs. 4 and 5 evaluate ORA. For every transmit-power point, each candidate RIS is first assigned the phase vector produced by the tested controller, after which the RIS maximizing the instantaneous SINR in (12) is selected. Thus, the selection stage accounts for both the desired channel and CCI rather than using desired cascaded amplitude alone.

The ORA curves are more tightly clustered than the ERA curves because only one RIS is activated and the best candidate is selected. At $P_s = 20$ dBm, the DNN obtains $P_{\text{out}} = 0.8979$ and $C = 0.494399$ b/s/Hz, compared with 0.8949 and 0.500097 b/s/Hz for DCA. The corresponding gaps are 3.0×10^{-3} in outage and

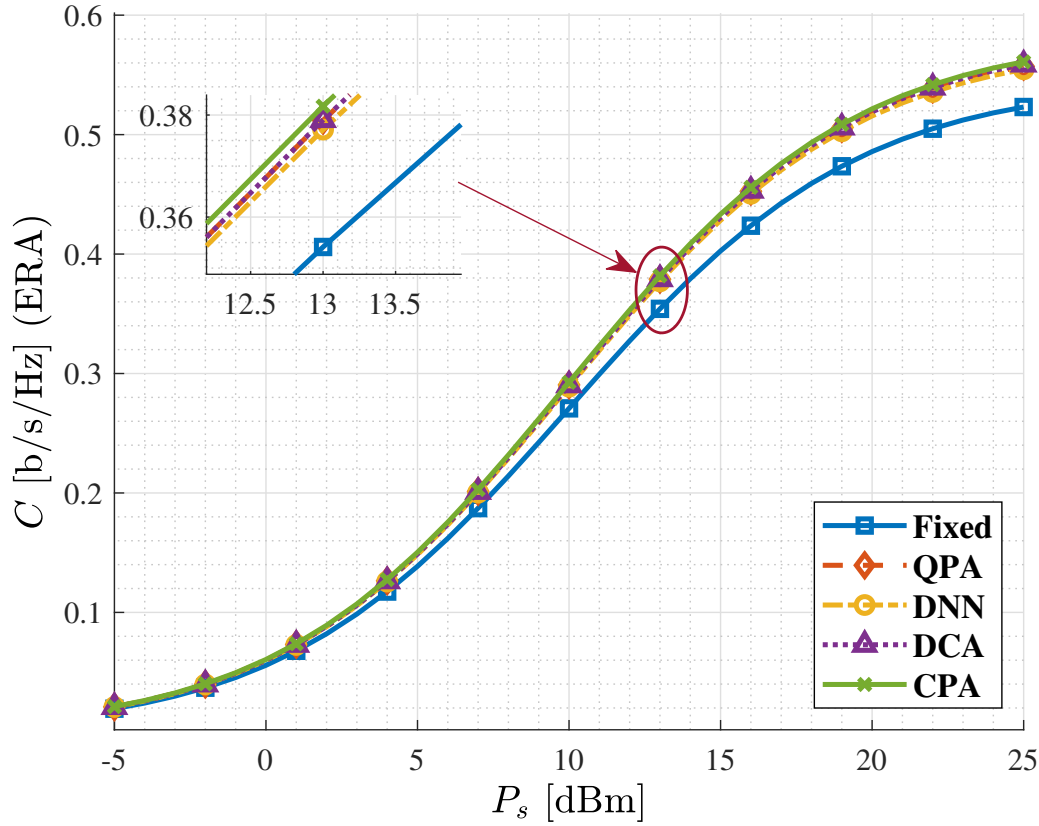


Figure 3. ERA ergodic capacity versus P_s under CCI for the five phase-control strategies.

5.698×10^{-3} b/s/Hz in capacity. At 25 dBm, the DNN gives $P_{\text{out}} = 0.8725$ and $C = 0.532209$ b/s/Hz, whereas DCA gives 0.8692 and 0.538545 b/s/Hz. The capacity gap is 0.006336 b/s/Hz, approximately 1.18% of the DCA capacity.

QPA again remains highly competitive: at 25 dBm it achieves $P_{\text{out}} = 0.8702$ and $C = 0.537643$ b/s/Hz. The DNN is therefore slightly below QPA in this setting, although its high-SNR SIR remains close to the teacher: the independent test gives a mean DCA–DNN SIR gap of 0.0843 dB, a median gap of 0.0690 dB, and a 90th-percentile gap of 0.1362 dB; 99.70% of the tested cases are within 0.5 dB of DCA. The ORA DNN outage floor and capacity ceiling are 0.8603 and 0.552909 b/s/Hz, compared with 0.8573 and 0.559649 b/s/Hz for DCA.

3.5. Learning Fidelity and Residual Diagnostics

The learning metrics clarify why exact phase-label accuracy and system utility should be reported together. For ERA, the QPA-residual targets are strongly imbalanced: approximately 90.02% of all coordinates require no DCA correction. Class balancing prevents the network from collapsing to the all-zero residual solution. On the held-out training-pipeline test split, the ERA element-wise residual accuracy is 85.25%. More importantly, on the independent system-level test set the DNN applies nonzero corrections to 6.54% of coordinates, whereas the DCA teacher modifies 10.00% of QPA coordinates, and the absolute DNN and DCA phase states match on 85.22% of coordinates. The held-out nonzero-residual detection recall is 11.82%, showing that the DNN captures only a subset of the sparse teacher corrections; nevertheless, the small 0.0435-dB mean SIR gap demonstrates that many missed phase-label corrections have limited impact on the global SIR objective.

For ORA, the absolute four-class labels are nearly balanced and the held-out element-wise phase accuracy is 48.73%. The independent system-level mean SIR gap of 0.0843 dB is again much more informative than exact vector accuracy because different 2-bit phase vectors can produce similar equivalent-channel utility.

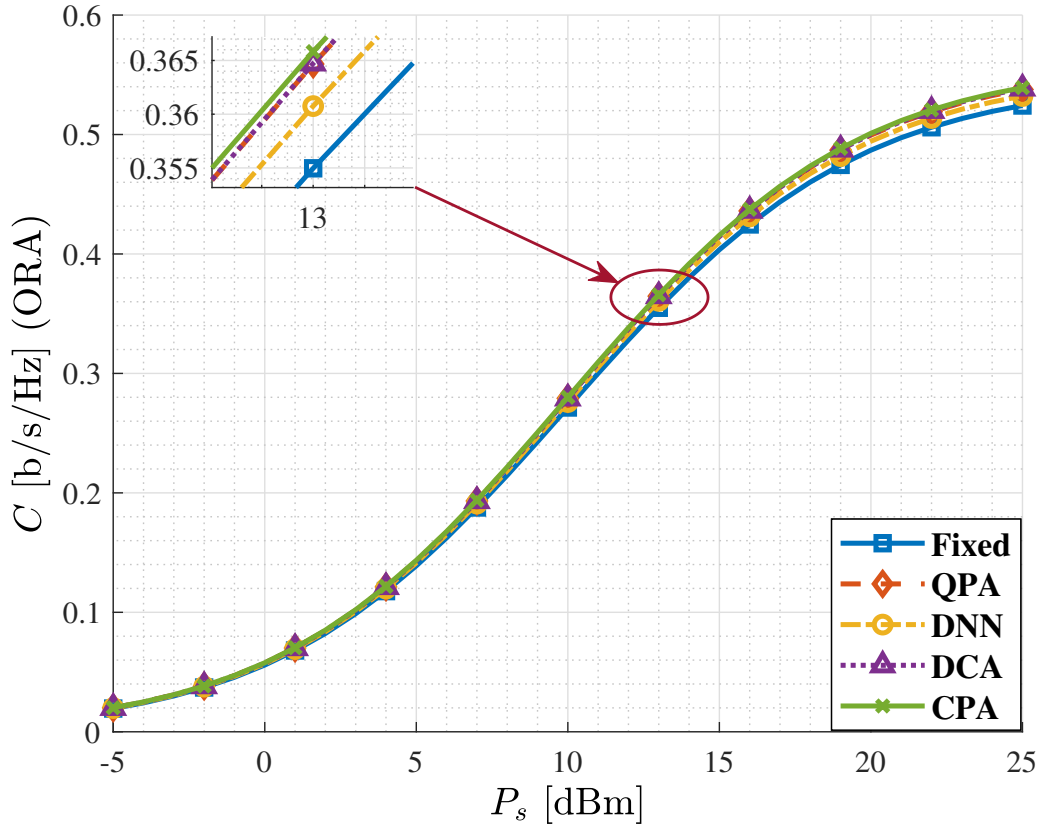


Figure 4. ORA outage probability versus P_s under CCI. The selected RIS maximizes the instantaneous SINR after applying the corresponding phase controller.

The selected checkpoints occur at epochs 93 and 33 for ERA and ORA, with CPU training times of 141.45 s and 41.38 s, respectively.

The measured MATLAB DCA execution times over 10^4 independent realizations were 3.969 s for ERA and 3.780 s for ORA, corresponding to approximately 0.397 ms per ERA realization and 0.378 ms per ORA realization including all three candidates. These wall-clock values are implementation- and hardware-dependent and are therefore reported only as reproducibility information; no unsupported wall-clock speedup claim is made for the DNN. The principal computational distinction remains that DCA performs channel-dependent coordinate iterations, whereas the trained DNN executes a fixed forward graph.

3.6. High-SNR Interpretation

The high-SNR analysis explains the outage floor and capacity saturation in both ERA and ORA. With the equal-power sweep, increasing P_s multiplies the desired and interfering received powers by the same factor. Once thermal noise becomes negligible, the SINR depends only on the random ratio in (39) for ERA or the selected ratio in (41) for ORA. Therefore,

$$\lim_{P_s \rightarrow \infty} P_{\text{out}}(P_s) = P_{\text{out}}^{\infty} > 0 \quad (49)$$

whenever a nonzero fraction of channel realizations has $\gamma^{\infty} < \gamma_{\text{th}}$. Likewise, $C(P_s)$ converges to the finite expectation in (43). Phase control can shift the limiting SIR distribution and thereby improve the floor/ceiling values, but it cannot change the interference-limited order when all three BS powers scale together.

The asymptotic results illustrate this point. For ERA, the DNN/DCA outage floors are 0.8482/0.8456 and the capacity ceilings are 0.576005/0.580444 b/s/Hz. For ORA, the corresponding values are 0.8603/0.8573 and 0.552909/0.559649 b/s/Hz. Thus, the DNN preserves most of the teacher's limiting utility but, as expected, does not eliminate the CCI-induced saturation.

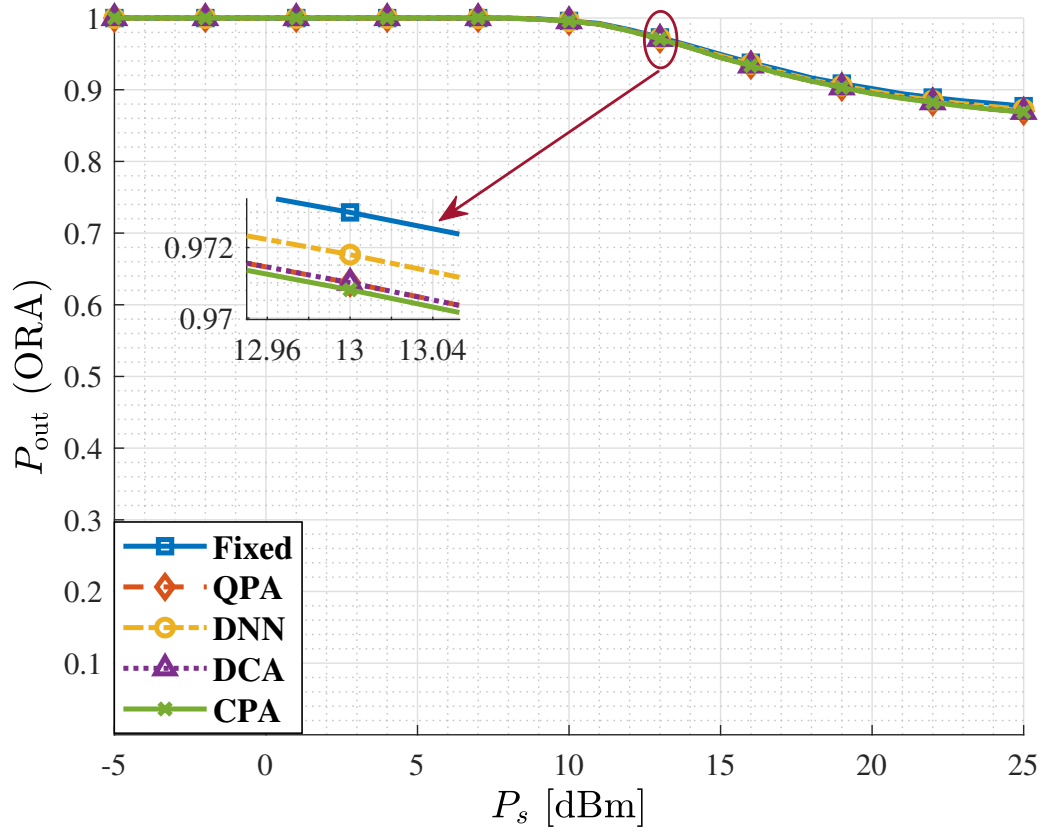


Figure 5. ORA ergodic capacity versus P_s under CCI for the five phase-control strategies.

3.7. Limitations

Four limitations should be stated explicitly. First, the learning model assumes that the required channel-derived features are available at the controller; it does not solve CSI acquisition. Second, DCA labels are coordinate-wise local optima rather than globally optimal ground truth. Third, the DCA teacher optimizes the high-SNR SIR because all BS powers scale together; at low transmit powers, a finite-noise SINR teacher could generate different phase decisions. Fourth, the ERA residual targets remain sparse and difficult to identify: despite class balancing, the held-out nonzero-residual recall is only 11.82%. The small utility gap indicates that this label mismatch has limited impact for the present geometry and channel distribution, but robustness to CSI errors, distribution shift, mobility, variable RIS sizes, and different interference regimes remains open.

4. CONCLUSION

This paper developed and evaluated a learning-assisted 2-bit phase-control framework for distributed multi-RIS downlinks under co-channel interference. The proposed method explicitly retains the CSI requirement and uses an interference-aware DCA teacher rather than desired-signal phase alignment alone. For ERA, the DNN learns class-balanced residual corrections relative to QPA and is trained with an additional SIR-gap utility term; checkpoint selection is performed only after the utility-aware stage becomes active. ORA uses absolute phase labels with the same physical utility principle. On the independent test set, the mean DCA–DNN high-SNR SIR gaps are 0.0435 dB for ERA and 0.0843 dB for ORA. At $P_s = 25$ dBm, the DNN capacities are 0.554677 b/s/Hz for ERA and 0.532209 b/s/Hz for ORA, within 0.004045 and 0.006336 b/s/Hz of DCA, respectively. QPA remains a strong low-complexity baseline and slightly outperforms the DNN at some finite-SNR operating points; the contribution of the DNN is therefore best understood as a fixed, iteration-free surrogate that preserves most of the interference-aware teacher utility rather than as a universally superior phase controller. The high-SNR derivations show that common scaling of the desired and interfering powers produces

finite SINR limits, nonzero outage floors, and capacity ceilings for both ERA and ORA. Future work will consider imperfect/pilot-based CSI, finite-SNR teacher objectives, distribution shift and mobility, topology-aware networks for variable-size RIS deployments, and label-free or quantization-aware learning.

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