Deep Learning-Based Energy Efficiency Maximization in Massive MIMO-NOMA Networks With Multiple RISs

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***Abstract*—In this paper, we study a deep learning (DL)-based energy efficiency maximization (EEM) problem in massive multiple-input multiple-output (MIMO)-non-orthogonal multiple access (NOMA) networks with multiple reconfigurable intelligent surfaces (RISs). These RISs are deployed randomly at the edge of the near radius to assist the base station (BS) in communicating with near and far users. We formulate the problem of jointly optimizing the precoding matrix and phase shift of the RISs to maximize the overall energy efficiency subject to the quality-of-service of each user, phase shift of RISs, and power budget of the BS constraints. To address this challenging non-convex problem with mixed-integer constraints, the original problem is decoupled into phase shift and beamforming sub-problems, then addressed them separately. We introduce the bisection search algorithm to address the challenge of the phase shifts optimization problem. For the beamforming optimization, it is transformed into an equivalent non-convex problem but with a more tractable form. Then, we propose an iterative algorithm based on the inner approximation method for its solution. To support real-time optimization, we design a deep learning framework to predict optimal solutions of phase shifts at RISs and precoding matrix under different parameter settings. Simulation results show that the proposed DL-based approach can predict the optimal solution with high accuracy in a short time compared to the conventional approach. Additionally, the effect of the maximum power budget at the base station, the number of RISs, and BS's antennas are evaluated thoroughly.**

***Index Terms*—Deep learning, energy efficiency, massive MIMO, NOMA, non-convex optimization, phase shift, RIS.**

I. Introduction

Massive multiple-input multiple-output (MIMO) is a promising technology to achieve high spectral efficiency (SE) [1] and energy efficiency (EE) [2] in the fifth generation (5G) wireless networks and beyond. As the number of users and antennas at the base station (BS) increases, the computational complexity rises, which poses challenges in determining resource allocation. To tackle this problem, deep learning (DL) has been widely studied to solve the resource allocation problems such as power allocation [3], channel estimation [4], pilot power allocation [5] and precoding matrix [6] in the massive MIMO networks within a short processing time. However, when the cell dimension increases or there is an obstacle between BS and users, the received signal quality of users may degrade.

To enhance the coverage area and improve the received signal quality of users, reconfigurable intelligent surface (RIS) has been proposed to cover a wide area and improve received signal quality for users since it has the ability to configure its elements flexibly [7]. However, it is difficult to obtain the optimal phase shift at RIS due to the large number of RIS elements. To tackle this problem, the authors in [6] proposed a DL-based framework to achieve the optimal phase shift at RISs in massive MIMO-non orthogonal multiple access (NOMA) networks. NOMA is one of the promising technologies for beyond 5G networks to improve SE and EE in massive MIMO networks [8]. The authors in [9] studied the DL-based method to evaluate the RIS-aided cognitive NOMA networks. By employing the DL-based method, the computational complexity is much reduced than that of the conventional optimization approaches.

Inspired by the potential synergy of massive MIMO-NOMA networks, RIS and DL technique, this paper studies an energy efficiency maximization problem in massive MIMO-NOMA networks, where multiple RISs are deployed to improve the received signal quality at users, accompanied by a DL-based evaluation framework. The advantage of integrating DL and RIS in massive MIMO-NOMA networks lies in their ability to improve system performance with low complexity and processing time. At the same time, there exists a gap in research exploring the effect of the combination of DL, RIS, and massive MIMO-NOMA networks to address the challenges of energy efficiency maximization problem. The main contributions of the paper can be summarized as follows:

- We consider a downlink multi-user massive MIMO-NOMA networks, where multiple RISs are deployed to improve the received quality signal of users. We formulate the energy efficiency maximization (EEM) problem subject to the minimum individual data rate, maximum power budget, and phase shift at the RIS. The formulated problem belongs to the class of non-linear mixed integer programming, which is very challenging to solve optimally.

- To solve the EEM problem, we decouple it into phase shift and beamforming sub-problems. Then, we address them sequentially with a proposed bisection algorithm and iterative algorithm based on IA method with low complexity for phase shift and beamforming sub-problems, respectively.
- To support real-time optimization, we design a DL-based framework to predict the optimal solution under different parameter settings within a short time and high accuracy.
- Simulation results show that the proposed DL-based framework can predict the optimal solution of the EEM problem within a short execution time. Additionally, the impacts of the maximum power budget at the BS, the number of RISs and BS's antennas are evaluated thoroughly.

Notation: Italic, bold-face lower case and upper-case letters are denoted by scalar, vectors, and matrices, respectively. The $\mathrm{diag}(\mathbf{A})$ denotes diagonal matrix, and $\|.\|$ denotes as Euclidean norm of $\mathbf{A}$. $\mathbb{C}$ and $\Re$ are denote complex numbers and real part, respectively.

II. System Model

A. System Description

We consider a downlink multiple-user in massive MIMO-NOMA networks assisted by multiple RISs as shown in Fig. 1. A BS is deployed to serve a set $\mathcal{K} = \{\mathrm{UE}_k | k = 1, \cdots, K\}$ of near user and a set $\mathcal{L} = \{\mathrm{UE}_l | l = 1, \cdots, L\}$ of far user simultaneously, while the N RISs (R) help to improve the signal quality of users. The BS, UE_k, and UE_l are equipped with $M_{\mathrm{BS}} > 1$, $M_K \geq 1$, $M_L \geq 1$ antennas, respectively, while each RIS is equipped with $M_{\mathrm{R}} > 1$ elements. We

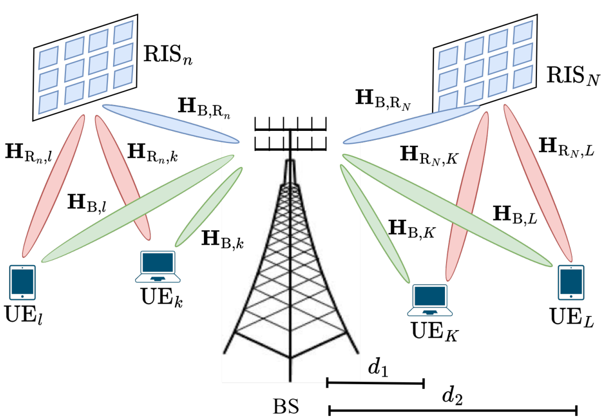


Fig. 1. The proposed system model of DL design EEM in massive MIMO-NOMA systems assisted multiple RIS.

assume that BS is located in the center of the cell, while UE_k, and UE_L are uniformly deployed with d_1 and d_2 radius from the BS, where $d_2 > d_1$. The RIS is deployed randomly at the edge of the d_1 [10]. We also assume the BS, UE_k and UE_l know the channel state information (CSI) perfectly [3]. Furthermore, the BS can calculate the transmit power to the users and phase shift at RIS. We also assume the reflected amplitude of the RIS is ideal; thus, it is set to one [6].

B. Channel Model

The BS transmits the superimposed signal to users following the NOMA principle, which can be expressed as

$$\mathbf{s} = \sum_{k}^{K} \mathbf{W}_k x_k + \sum_{l}^{L} \mathbf{W}_l x_l, \tag{1}$$

where $\mathbf{W}_k$ and $\mathbf{W}_l$ are the linear precoding matrices of user k and user l, respectively, while x_k and x_l denote the k-th near and l-th far user's symbols. For the sake of notation, we define $\mathbf{W}_1 \triangleq [\mathbf{W}_k]_{k\in\mathcal{K}}$, $\mathbf{W}_2 \triangleq [\mathbf{W}_l]_{l\in\mathcal{L}}$, and $\mathbf{W} \triangleq [\mathbf{W}_1\mathbf{W}_2]$. Let $\mathbf{H}_{B,k}$, $\mathbf{H}_{B,l}$ and $\mathbf{H}_{B,\mathrm{R}_n}$ be the channel gains from BS to UE_k, UE_l, and R_n, respectively. $\mathbf{H}_{\mathrm{R}_n,k}$ and $\mathbf{H}_{\mathrm{R}_n,l}$ are the channel gains from R_n to the UE_k and UE_l, respectively. And $\mathbf{\Theta}_{\mathrm{R}_n}$ is the phase shift matrix of R_n with diagonal reflecting matrix being $\mathbf{\Theta} = \mathrm{diag}(\phi_{\mathrm{R}_n,1}, \phi_{\mathrm{R}_n,2}, \cdot, \phi_{\mathrm{R}_n,M_{\mathrm{R}}})$, where $\phi_{\mathrm{R}_n,M_{\mathrm{R}}} = e^{j\theta_{\mathrm{R}_n,M_{\mathrm{R}}}}$ with $\phi_{\mathrm{R}_n,M_{\mathrm{R}}} \in (0, 2\pi]$. Then, the equivalent channel gains from BS to UE_k, $\hat{\mathbf{H}}_{\mathrm{B},k}(\mathbf{\Theta})$ and UE_l, $\hat{\mathbf{H}}_{\mathrm{B},l}(\mathbf{\Theta})$, can be presented, respectively, as

$$\hat{\mathbf{H}}_{\mathrm{B},k}(\mathbf{\Theta}) = \mathbf{H}_{\mathrm{B},k} + \sum_{n}^{N} \mathbf{H}_{\mathrm{B,R}_n} \mathbf{\Theta}_{\mathrm{R}_n} \mathbf{H}_{\mathrm{R}_n,k}, \tag{2}$$

$$\hat{\mathbf{H}}_{\mathrm{B},l}(\mathbf{\Theta}) = \mathbf{H}_{\mathrm{B},l} + \sum_{n}^{N} \mathbf{H}_{\mathrm{B,R}_n} \mathbf{\Theta}_{\mathrm{R}_n} \mathbf{H}_{\mathrm{R}_n,l}, \tag{3}$$

where the channel gain $\mathbf{H} \triangleq \sqrt{\lambda_h}\tilde{\mathbf{H}}$ with $\tilde{\mathbf{H}} \in \{\mathbf{H}_{\mathrm{B},k}, \mathbf{H}_{\mathrm{B},l}, \mathbf{H}_{\mathrm{B,R}_n}, \mathbf{H}_{\mathrm{R}_n,k}, \mathbf{H}_{\mathrm{R}_n,l}\}$, where λ_h is the large and $\tilde{\mathbf{H}}$ is the small scale fadings, respectively [11]. Considering the flat fading channels, the received signals at UE_k and UE_l can be expressed as

$$\begin{aligned}\mathbf{y}_k = {} & \hat{\mathbf{H}}_{\mathrm{B},k}(\mathbf{\Theta})\mathbf{W}_k x_k + \sum_{k'\in\mathcal{K}\setminus\{k\}} \hat{\mathbf{H}}_{\mathrm{B},k}(\mathbf{\Theta})\mathbf{W}_{k'} x_{k'} \\ & + \sum_{l\in\mathcal{L}} \hat{\mathbf{H}}_{\mathrm{B},k}(\mathbf{\Theta})\mathbf{W}_l x_l + \mathbf{n}_k, \end{aligned} \tag{4}$$

$$\begin{aligned}\mathbf{y}_l = {} & \hat{\mathbf{H}}_{\mathrm{B},l}(\mathbf{\Theta})\mathbf{W}_l x_l + \sum_{l'\in\mathcal{L}\setminus\{l\}} \hat{\mathbf{H}}_{\mathrm{B},l}(\mathbf{\Theta})\mathbf{W}_{l'} x_{l'} \\ & + \sum_{k\in\mathcal{K}} \hat{\mathbf{H}}_{\mathrm{B},k}(\mathbf{\Theta})\mathbf{W}_k x_k + \mathbf{n}_l, \end{aligned} \tag{5}$$

where $\mathbf{n}_k$ and $\mathbf{n}_l$ denote a white Gaussian noise vector at UE_k and UE_l with variance σ^2. The UE_k performs the successive interference cancellation (SIC) to detect the UE_l signal. Thus, the signal-to-interference plus noise ratio (SINR) at UE_k in decoding UE_l's signal can be expressed as

$$\gamma_k^{x_l}(\mathbf{W}, \mathbf{\Theta}) = \frac{\|\hat{\mathbf{H}}_{B,k}(\mathbf{\Theta})\mathbf{W}_l\|}{\Psi_{k,l}(\mathbf{W}, \mathbf{\Theta})}, \tag{6}$$

where

$$\begin{aligned}\Psi_{k,l}(\mathbf{W}, \mathbf{\Theta}) = {} & \sum_{l'\in\mathcal{L}\setminus\{l\}} \|\hat{\mathbf{H}}_{B,k}(\mathbf{\Theta})\mathbf{W}_{l'}\|^2 \\ & + \sum_{k\in\mathcal{K}} \|\hat{\mathbf{H}}_{B,k}(\mathbf{\Theta})\mathbf{W}_k\|^2 + \sigma_k^2. \end{aligned} \tag{7}$$

Furthermore, the SINR of UE_k to decode its own message can be expressed as

$$\gamma_k^{x_k}(\mathbf{W}, \mathbf{\Theta}) = \frac{\|\hat{\mathbf{H}}_{B,k}(\mathbf{\Theta})\mathbf{W}_k\|}{\Psi_{k,k}(\mathbf{W}, \mathbf{\Theta})}, \tag{8}$$

where

$$\Psi_{k,k}(\mathbf{W}, \mathbf{\Theta}) = \sum_{l' \in \mathcal{L}} \|\hat{\mathbf{H}}_{B,k}(\mathbf{\Theta})\mathbf{W}_{l'}\|^2 + \sum_{k' \in \mathcal{K} \setminus \{k\}} \|\hat{\mathbf{H}}_{B,k}(\mathbf{\Theta})\mathbf{W}_{k'}\|^2 + \sigma_k^2. \tag{9}$$

For UE_l, the UE_l can decode directly its own signal by using SINR, which can be expressed as

$$\gamma_l^{x_l}(\mathbf{W}, \mathbf{\Theta}) = \frac{\|\hat{\mathbf{H}}_{B,l}(\mathbf{\Theta})\mathbf{W}_l\|}{\Psi_{l,l}(\mathbf{W}, \mathbf{\Theta})}, \tag{10}$$

where

$$\Psi_{l,l}(\mathbf{W}, \mathbf{\Theta}) = \sum_{l' \in \mathcal{L} \setminus \{l\}} \|\hat{\mathbf{H}}_{B,l}(\mathbf{\Theta})\mathbf{W}_{l'}\|^2 + \sum_{k \in \mathcal{K}} \|\hat{\mathbf{H}}_{B,l}(\mathbf{\Theta})\mathbf{W}_k\|^2 + \sigma_l^2, \tag{11}$$

The downlink channel capacity of UE_k and UE_l can be calculated, respectively, as

$$\mathcal{R}_k(\mathbf{W}, \mathbf{\Theta}) = \ln(1 + \gamma_k^{x_k}(\mathbf{W}, \mathbf{\Theta})), \quad \forall k \in \mathcal{K}, \tag{12}$$

$$\mathcal{R}_l(\mathbf{W}, \mathbf{\Theta}) = \ln(1 + \gamma_l^{x_l}(\mathbf{W}, \mathbf{\Theta})), \quad \forall l \in \mathcal{L}. \tag{13}$$

C. Problem formulation

Considering the EEM problem, the total hardware power consumption at BS and all users can be expressed as [11]

$$P_{\sum} = \epsilon^{-1}(\|\mathbf{W}_1\|^2 + \|\mathbf{W}_2\|^2) + M_{\mathrm{BS}} P_{\mathrm{BS}}^d + P_{\mathrm{BS}}^s + \sum_{k \in \mathcal{K}} M_k P_k^s + \sum_{l \in \mathcal{L}} M_l P_l^s, \tag{14}$$

where $\epsilon \in (0, 1]$ is the transmit power efficiency, P_{BS}^d represents the dynamic power consumption, correlating to the power radiation across all circuit blocks within each active radio-frequency chain, P_{BS}^s denotes the static power used by the cooling system, P_k^s and P_l^s represent the hardware static power of UE_k and UE_l. Let assume that the total circuit power is $P_0 \triangleq M_{\mathrm{BS}} P_{\mathrm{BS}}^d + P_{\mathrm{BS}}^s + \sum_{k \in \mathcal{K}} M_k P_k^s + \sum_{l \in \mathcal{L}} M_l P_l^s$.

The main goal of this paper is to maximize energy efficiency of the considered system by optimizing the precoding matrix and phase shift at RISs subject to individual channel capacity constraints, maximum total power at BS and phase shift matrix at RIS. Thus, the EEM problem can be formulated as

$$\max_{\mathbf{W}, \mathbf{\Theta}} \quad \text{EEM}_{\sum} \triangleq \frac{\sum_{k \in \mathcal{K}} \mathcal{R}_k(\mathbf{W}, \mathbf{\Theta}) + \sum_{l \in \mathcal{L}} \mathcal{R}_l(\mathbf{W}, \mathbf{\Theta})}{\epsilon^{-1}(\|\mathbf{W}_1\|^2 + \|\mathbf{W}_2\|^2) + P_0} \tag{15a}$$

$$\text{s.t.} \quad \mathcal{R}_k(\mathbf{W}, \mathbf{\Theta}) \geq \bar{\mathsf{R}}_k, \quad \forall k \in K, \tag{15b}$$

$$\mathcal{R}_l(\mathbf{W}, \mathbf{\Theta}) \geq \bar{\mathsf{R}}_l, \quad \forall l \in L, \tag{15c}$$

$$||\mathbf{W}_k||^2 + ||\mathbf{W}_l||^2 \leq P_{\mathrm{BS}}^{\max}, \tag{15d}$$

$$(\theta_{\mathrm{R}_n} | 0 \leq \theta_{\mathrm{R}_n} \leq 2\pi], \quad \forall j \in J, \tag{15e}$$

where constraints (15b) and (15c) guarantee the channel capacity for UE_k and UE_l must be greater than the minimum requirement $\bar{\mathsf{R}}_k \geq 0$ and $\bar{\mathsf{R}}_l \geq 0$, respectively. Constraint (15d) represents the total power of all users in the system, which is upper bounded by the maximum power budget at BS. And constraint (15e) represents the phase shift of the RIS that has discrete values. Thus, it is clear that the objective function in (19a) is non-convex with respect to $\mathbf{W}_1$, $\mathbf{W}_2$ and $\mathbf{\Theta}$. The EEM problem belongs to the class of mixed-integer non-convex programming class, which is very difficult to solve and obtain its optimal solution.

III. The proposed Algorithm for Energy Efficiency Maximization Problem

Generally, solving problem (15) is more challenging than the spectral efficiency maximization (SEM) problem in [6] due to mixed integer non-convex fraction programming, which requires exponential complexity to find the optimal solution. Nevertheless, we will show that the IA method can solve the EEM problem effectively through our new transformations. In particular, we decouple problem (15) into phase shift and beamforming optimization sub-problems and then solve them sequentially [12].

A. Proposed Algorithm for Phase Shift Sub-Problem

To address the phase shift optimization problem, the beamforming variable part is fixed. Then, the problem (15) can be re-written as

$$\max_{\mathbf{\Theta}} \quad \text{EEM}_{\sum} \triangleq \frac{\sum_{k \in \mathcal{K}} \mathcal{R}_k(\mathbf{\Theta})}{\epsilon^{-1}(K + L) + P_0} + \frac{\sum_{l \in \mathcal{L}} \mathcal{R}_l(\mathbf{\Theta})}{\epsilon^{-1}(K + L) + P_0} \tag{16a}$$

$$\text{s.t.} \quad (15e). \tag{16b}$$

As we can see in problem (16), the objective function (16a) is concave, while constraint (16b) is a linear constraint. The bisection search will be efficient to solve the convex problem, which is proposed in Algorithm 1.

Algorithm 1 Bisection Search algorithm to Solve sub-Problem (16)

Input: k, l.
Output: $\mathbf{\Theta}_{\mathrm{R}_n}^{\star}$.
Initialize the lower p_{L}, upper bound p_{U}, and accuracy ε;
1: Calculate $p = (p_{\mathsf{L}} + p_{\mathsf{U}})/2$;
2: Update $\phi_{\mathrm{R}_n}(p_r)$;
3: Solve the problem (16);
4: **if** Convergence **then**
5: $\quad\mathbf{\Theta}_{\mathsf{R}_k}^{\star} \leftarrow \mathbf{\Theta}_{\mathsf{R}_k}$;
6: **end if**

Once the optimal solution of the phase shift optimization problem is obtained, the beamforming optimization sub-problem will be addressed sequentially, which will be presented in the following sub-section.

B. Proposed Algorithm for Beamforming Sub-Problem

In this sub-section, we apply the IA method to approximate the non-convex parts iteratively. We first introduce a new variable $\Delta > 0$ which satisfies the constraint

$$\epsilon^{-1}(\|\mathbf{W}_1\|^2 + \|\mathbf{W}_2\|^2) + P_0 \le \Delta, \tag{17}$$

then, with the optimal solution of the phase shift optimization problem, the problem (15) is equivalently re-written as

$$\max_{\mathbf{W},\boldsymbol{\Delta}} \quad \mathrm{EEM}_{\sum} \triangleq \sum_{k\in\mathcal{K}} \frac{\mathcal{R}_k(\mathbf{W})}{\Delta} + \sum_{l\in\mathcal{L}} \frac{\mathcal{R}_l(\mathbf{W})}{\Delta} \tag{18a}$$

$$\text{s.t.} \quad \text{(15b) (15c) (15d)} \tag{18b}$$

We introduce new variables $\mathbf{e} \triangleq \{e_k, e_l\}_{k\in\mathcal{K},l\in\mathcal{L}}$ and $\boldsymbol{\gamma} \triangleq \{\gamma_k, \gamma_l\}_{k\in\mathcal{K},l\in\mathcal{L}}$, where $\mathbf{e}$ and $\boldsymbol{\gamma}$ are the soft energy efficiencies and SINRs of UE_k and UE_l, respectively. Thus, problem (18) can be equivalently expressed as

$$\max_{\mathbf{W},\boldsymbol{\Delta},\boldsymbol{\gamma},\mathbf{e}} \quad \mathrm{EEM}_{\sum} \triangleq \sum_{k\in\mathcal{K}} e_k + \sum_{l\in\mathcal{L}} e_l \tag{19a}$$

$$\text{s.t.} \quad \gamma_k^{x_k}(\mathbf{W}) \ge 1/\gamma_k, \tag{19b}$$

$$\gamma_l^{x_l}(\mathbf{W}) \ge 1/\gamma_l, \tag{19c}$$

$$\ln(1+1/\gamma_k)/\Delta \ge e_k, \tag{19d}$$

$$\ln(1+1/\gamma_l)/\Delta \ge e_l, \tag{19e}$$

$$\ln(1+1/\gamma_k) \ge \bar{\mathsf{R}}_k, \tag{19f}$$

$$\ln(1+1/\gamma_l) \ge \bar{\mathsf{R}}_l, \tag{19g}$$

$$\text{(15d)}, \ \text{(17)}. \tag{19h}$$

To obtain a tractable form, we introduce $\boldsymbol{\iota} \triangleq \{\iota_{k,l} > 0\}_{k\in\mathcal{K},l\in\mathcal{L}}$ which satisfy the convex constraint $\|\hat{\mathbf{H}}_{\mathrm{B},k}\mathbf{W}_{l'}\|^2 \le \iota_{k,l'}$. Furthermore, by using Lemmas 1 and 2 in [11], the constraint (19b) can be approximated at the κ-th iteration as

$$\frac{\hat{\Psi}_{k,k}(\mathbf{W})}{\gamma_k} \le f_k^{(\kappa)}(\mathbf{W}_k) \tag{20}$$

where

$$\|\hat{\mathbf{H}}_{\mathrm{B},k}\mathbf{W}_k\|^2 \ge 2\Re\{(\hat{\mathbf{H}}_{\mathrm{B},k}\mathbf{W}_k^{(\kappa)})^*(\hat{\mathbf{H}}_{\mathrm{B},k}\mathbf{W}_k)\} - \|\hat{\mathbf{H}}_{\mathrm{B},k}\mathbf{W}_k^{(\kappa)}\|^2 \triangleq f_k^{(\kappa)}(\mathbf{W}_k), \tag{21}$$

$$\hat{\Psi}_{k,k}(\mathbf{W}) \le \sum_{l'\in\mathcal{L}} \left(\frac{\Delta_{k,l'}^2}{2\Delta_{k,l'}^{(\kappa)}} + \frac{\Delta_{k,l'}^{(\kappa),2}}{2} \right) + \sum_{k'\in\mathcal{K}\setminus\{k\}} \|\hat{\mathbf{H}}_{\mathrm{B},k}\mathbf{W}_{k'}\|^2 + \sigma_k^2. \tag{22}$$

Similar to (20), constraint (19c) can be approximated as

$$\frac{\Psi_{l,l}(\mathbf{W})}{\gamma_l} \le f_l^{(\kappa)}(\mathbf{W}_l), \tag{23}$$

where

$$\|\hat{\mathbf{H}}_{\mathrm{B},l}\mathbf{W}_l\|^2 \ge 2\Re\{(\hat{\mathbf{H}}_{\mathrm{B},l}\mathbf{W}_l^{(\kappa)})^*(\hat{\mathbf{H}}_{\mathrm{B},l}\mathbf{W}_l)\} - \|\hat{\mathbf{H}}_{\mathrm{B},l}\mathbf{W}_l^{(\kappa)}\|^2 \triangleq f_l^{(\kappa)}(\mathbf{W}_l) \tag{24}$$

The function $\ln(1+1/\gamma)/\Delta$ is convex in (γ, Δ) in constraints (19d) and (19e), which can be approximated at $(\gamma^{(\kappa)}, \Delta^{(\kappa)})$ point as [13, Eq. (18)]

$$\frac{\ln(1+1/\gamma)}{\Delta} \ge \frac{2\ln(1+1/\gamma^{(\kappa)})}{\Delta^{(\kappa)}} + \frac{1}{\Delta^{(\kappa)}(\gamma^{(\kappa)}+1)} - \frac{\gamma}{\Delta^{(\kappa)}\gamma^{(\kappa)}(\gamma^{(\kappa)}+1)} - \frac{\ln(1+1/\gamma^{(\kappa)})\Delta}{(\Delta^{(\kappa)})^2} \triangleq \mathcal{A}^{(\kappa)}(\gamma,\Delta), \ \forall \Delta^{(\kappa)} > 0, \ \gamma^{(\kappa)} > 0. \tag{25}$$

For constraints (19f) and (19g), they can be approximated as [6, Eq. (34)]

$$\ln(1+1/\gamma) \ge \ln(1+(\gamma^{(\kappa)})^{-1}) + (\gamma^{(\kappa)}+1)^{-1} - \gamma[\gamma^{(\kappa)}(\gamma^{(\kappa)}+1)]^{-1} \triangleq \mathcal{B}^{(\kappa)}(\gamma). \tag{26}$$

Based on the discussion above, we can approximate the problem (19) by the following convex problem at iteration $\kappa+1$:

$$\max_{\mathbf{W},\boldsymbol{\Delta},\boldsymbol{\gamma},\mathbf{e}} \quad \mathrm{EEM}_{\sum} \triangleq \sum_{k\in\mathcal{K}} e_k + \sum_{l\in\mathcal{L}} e_l \tag{27a}$$

$$\text{s.t.} \quad \|\hat{\mathbf{H}}_{\mathrm{B},k}\mathbf{W}_{l'}\|^2 \le \iota_{k,l'}, \quad \forall k\in\mathcal{K}, \ l'\in\mathcal{L} \tag{27b}$$

$$\mathcal{A}^{(\kappa)}(\gamma_k,\Delta) \ge e_k, \quad \forall k\in\mathcal{K}, \tag{27c}$$

$$\mathcal{A}^{(\kappa)}(\gamma_k,\Delta) \ge e_l, \quad \forall l\in\mathcal{L}, \tag{27d}$$

$$\mathcal{B}^{(\kappa)}(\gamma_k) \ge \bar{\mathsf{R}}_k, \quad \forall k\in\mathcal{K}, \tag{27e}$$

$$\mathcal{B}^{(\kappa)}(\gamma_l) \ge \bar{\mathsf{R}}_l, \quad \forall l\in\mathcal{L}, \tag{27f}$$

$$\text{(15d)}, \ \text{(17)}, \ \text{(20)}, \ \text{(23)}. \tag{27g}$$

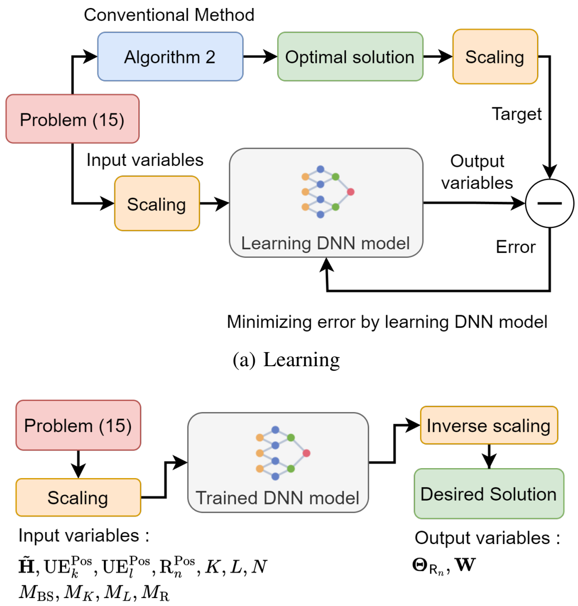
Finally, we summarize the proposed low-complexity iterative algorithm in Algorithm 2 which re-used Algorithm 1.

Algorithm 2 : IA-based Algorithm to Solve Problem (15)

Initialization: Set $\kappa \leftarrow 0$, $(\mathbf{W}, \boldsymbol{\Theta}) \leftarrow 0$, and generate an feasible point $(\mathbf{W}^{(0)}, \boldsymbol{\Delta}^{(0)}, \boldsymbol{\gamma}^{(0)}, \boldsymbol{\iota}^{(0)})$ randomly;
repeat
  Find $\boldsymbol{\Theta}^\star$, by using Algorithm 1;
  Solve convex problem (27) to obtain $(\mathbf{W}^\star, \boldsymbol{\Delta}^\star, \boldsymbol{\gamma}^\star, \boldsymbol{\iota}^\star)$;
  $(\mathbf{W}^{(\kappa+1)}, \boldsymbol{\Delta}^{(\kappa+1)}, \boldsymbol{\gamma}^{(\kappa+1)}, \boldsymbol{\iota}^{(\kappa+1)}) \leftarrow (\mathbf{W}^\star, \boldsymbol{\Delta}^\star, \boldsymbol{\gamma}^\star, \boldsymbol{\iota}^\star)$;
  $\kappa \leftarrow \kappa + 1$;
until Convergence
$(\mathbf{W}^\star, \boldsymbol{\Theta}^\star) \leftarrow (\mathbf{W}^{(\kappa)}, \boldsymbol{\Theta}^{(\kappa)})$;
Calculate $\mathrm{EEM}_{\sum}$ in (19a) based on $(\mathbf{W}^\star, \boldsymbol{\Theta}^\star)$;
Output: $\mathrm{EEM}_{\sum}$ and $(\mathbf{W}^\star, \boldsymbol{\Theta}^\star)$.

IV. Deep Learning Design for EEM Problem

In this section, we propose the DL-based framework for EEM problem in massive MIMO-NOMA networks assisted by multiple RISs. Fig. 2 illustrates the proposed DL-based framework including the training and testing phases to achieve the optimal solution of precoding matrix and phase shift of the STAR-RIS with low computational complexity and real-time manner. In Fig. 2(a), the DNN learns by off-line the mapping function between the input parameters of problem (15) and



(a) Learning

(b) Testing

Fig. 2. The proposed DL-based framework to predict the optimal values

optimal solution through solving the problem (15) by Algorithm 2 as target parameters. By using adaptive moment estimation (Adam) [14] on the training dataset, the DNN model is learning by minimizing errors in bias and weight of the model parameters. Once the learning process is completed, the trained model can predict the optimal values with new input data as shown in Fig. 2(b). Based on these processes, the DNN model learns to predict the optimal solution of the precoding matrix and phase shift of the RIS based on new input parameters.

The proposed architecture of a fully connected DNN is designed to address the precoding matrix and phase shift of the RIS as shown in Fig. 3. We consider small-scale fading

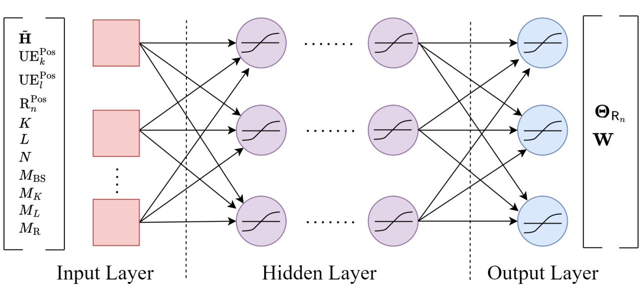


Fig. 3. The architecture of the DNN model.

matrices $\tilde{\mathbf{H}}$, user's positions $\{\mathrm{UE}_k^{\mathrm{Pos}}, \mathrm{UE}_l^{\mathrm{Pos}}\}$, the number of users $\{K, L\}$, RISs N, BS's antennas M_{BS}, user's antennas $\{M_K, M_L\}$ and elements at the RIS M_{R} as input parameters of the DNN model, while we consider the precoding matrix and phase shift of the RIS as output parameters. Thus, the DNN model consists of $7 + (2 \times 1) \times 3 + (M_{\mathrm{BS}} \times M_K) + (M_{\mathrm{BS}} \times M_L) + (M_{\mathrm{BS}} \times M_{\mathrm{R}}) \times 2 + (M_{\mathrm{R}} \times M_K) + (M_{\mathrm{R}} \times M_L)$ dimentional input layer. A fully connected of 4 hidden layers with 128, 256, 256, 128 neurons have weights along with rectified linear unit (ReLU) as activation functions. The output layer has $M_{\mathrm{BS}} + (M_{\mathrm{R}} \times 2)$ dimentional.

V. Simulation Results

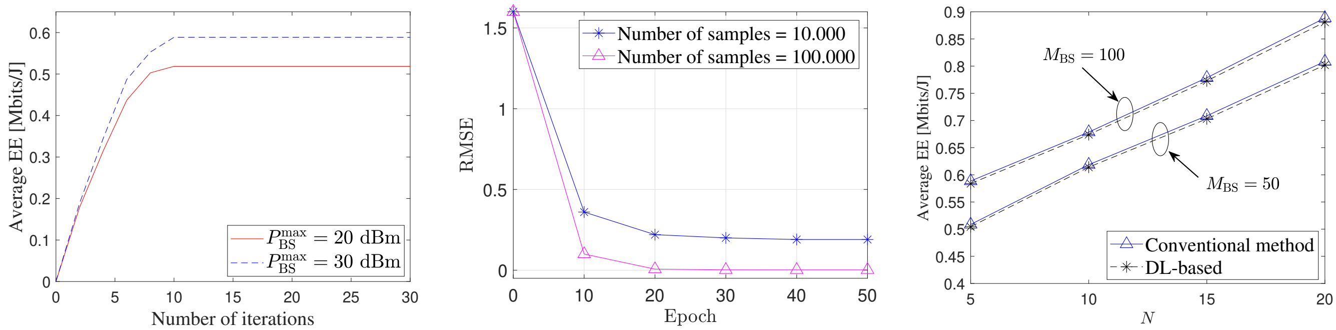
In this section, the illustrative simulation results are presented to demonstrate the performance of the proposed algorithms to solve the EEM problem in massive MIMO-NOMA networks assisted by multiple RISs. Simulation parameters for performance evaluation are set as follows: $\bar{\mathsf{R}}_k = \bar{\mathsf{R}}_l$ = 1 bps/Hz, cell dimension 500 m $\times$ 500 m, d_1 = 200 m, M_{R} = 16, M_{BS} = 50 and 100, $M_K = M_L$ = 10, $P_{\mathrm{BS}}^{\max}$ = 10 and 15 dBm, and $P_k^s = P_l^s$ = 5 dBm. The convex solver SDPT3 and the YALMIP toolbox are used in the MATLAB environment to solve the convex problem [6]. We generate the 100K dataset to learn the DNN model. For testing, we generate 500 new datasets to evaluate the performance of the DNN model when predicting the optimal solution.

Fig. 4(a) shows the effectiveness of Algorithm 2 to solve problem (15) with various maximum power budgets at BS. As can be observed in Fig. 4(a), the proposed algorithm converges to the optimal value within 13 iterations because it can find the improved solution over the whole feasible value in every iteration. Additionally, when the maximum power budget increases, the average EE increases because the EE performance is proportional to the channel capacity performance, which corresponds to objective function (19a).

Fig. 4(b) illustrates the impact of the epoch on the root mean square error (RMSE) with a variation the number of datasets. As we can see in Fig. 4(b), the RMSE decreases when the epoch value increases. One of the reasons is that the DNN updates the weight and bias of the neurons during the learning process. Besides that, the DNN model with a large number of samples performs better than its counterpart with a small number of samples because the DNN model can learn more features from a large number of samples.

Fig. 4(c) reveals the average EE versus the number of RISs N with a variation in the number of BS's antennas. When the number of RISs increases, the average EE increases because by increasing the number of RIS, the received signal quality of users can improve. Furthermore, when the number of BS's antennas increases, the average EE increases. The reason is that the system performance increases due to the increasing contribution of degrees of freedom (DoF). In addition, the DL-based approach can predict the optimal value of the precoding matrix and phase shift at the RIS with high accuracy so that it can achieve a good EE performance.

Finally, we evaluate the execution time of the DL-based approach to achieve the optimal solution as shown in Table I. As can be observed in Table I, the DL-based approach achieves the optimal solution with a short execution time even when the number of users increases. In contrast, the conventional approach achieves the optimal solution with a longer execution time when the number of users increases. The reason is that the DL-based approach uses the mapping function to



(a) Convergence of Alg. 2 with different $P_{\rm BS}^{\rm max}$ (b) Impact of the number of samples on the RMSE (c) Average EE vs N

Fig. 4. Convergence of Alg. 2, RMSE versus epoch and impact of N on the average EE

TABLE I
THE EXECUTION TIME OF CONVENTIONAL APPROACH VERSUS DL APPROACH

Number of UEs	6	10	14	18
Conventional approach [minutes]	1	2	3	7
DL-based approach [seconds]	1	1	1	1

predict the optimal value. On the other hand, the conventional approach needs several iterations when Algorithm 2 is running to achieve the optimal solution, thus it consumes a significantly greater amount of time compared to the DL-based approach.

VI. CONCLUSIONS

This paper studied a deep learning-based energy efficiency maximization problem in massive MIMO-NOMA networks assisted by multiple RISs to improve EE in the system. We considered the problem of jointly optimizing the precoding matrix of the RISs subject to the mixed integer constraints. To address this problem, we decoupled the formulated problem into phase shift and beamforming optimization problems. The bisection search algorithm was proposed to tackle the phase shift optimization problem, and also the low-complexity iterative algorithm was proposed to tackle the beamforming optimization problem, which was guaranteed convergence at less local optima. Towards real-time optimization, a DL-based framework was designed to predict the optimal value of the EEM problem according to small-scale fading, user's positions, the number of users, RISs, BS's antennas, and elements at the RIS. Furthermore, the proposed DL-based approach provided a high accuracy in a short time to predict the optimal values. Additionally, the impact of the maximum power budget at the BS, the number of RISs and BS's antennas were evaluated thoroughly.

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REFERENCES

[1] R. H. Y. Perdana, T.-V. Nguyen, and B. An, "A Deep Learning Design for Spectral Efficiency Maximization in Multi-IRS-aided Massive MIMO Systems," in *10th Int. Conf. Green Hum. Inf. Technol.*, Jeju Island, Korea, 2022, pp. 126–131.

[2] L. You, J. Xiong, X. Yi, J. Wang, W. Wang, and X. Gao, "Energy Efficiency Optimization for Downlink Massive MIMO with Statistical CSIT," *IEEE Trans. Wirel. Commun.*, vol. 19, no. 4, pp. 2684–2698, 2020.

[3] R. H. Y. Perdana, T. V. Nguyen, and B. An, "Deep neural network design with SLNR and SINR criterions for downlink power allocation in multi-cell multi-user massive MIMO systems," *ICT Express*, no. January, 2022.

[4] M. Soltani, V. Pourahmadi, A. Mirzaei, and H. Sheikhzadeh, "Deep Learning-Based Channel Estimation," *IEEE Commun. Lett.*, vol. 23, no. 4, pp. 652–655, 2019.

[5] J. Xu, P. Zhu, J. Li, and X. You, "Deep Learning-Based Pilot Design for Multi-User Distributed Massive MIMO Systems," *IEEE Wirel. Commun. Lett.*, vol. 8, no. 4, pp. 1016–1019, 2019.

[6] R. H. Y. Perdana, T.-V. Nguyen, and B. An, "Adaptive User Pairing in Multi-IRS-aided Massive MIMO-NOMA Networks: Spectral Efficiency Maximization and Deep Learning Design," *IEEE Trans. Commun.*, vol. 71, no. 7, pp. 4377–4390, 2023.

[7] Q. Wu and R. Zhang, "Towards Smart and Reconfigurable Environment: Intelligent Reflecting Surface Aided Wireless Network," *IEEE Commun. Mag.*, vol. 58, no. 1, pp. 106–112, nov 2020.

[8] X. Tian, Y. Huang, S. Verma, M. Jin, U. Ghosh, K. M. Rabie, and D. T. Do, "Power allocation scheme for maximizing spectral efficiency and energy efficiency tradeoff for uplink NOMA systems in B5G/6G," *Phys. Commun.*, vol. 43, p. 101227, 2020.

[9] T.-H. Vu, T.-V. Nguyen, D. B. da Benevides, and S. Kim, "Reconfigurable Intelligent Surface-Aided Cognitive NOMA Networks : Performance Analysis and Deep Learning Evaluation," *IEEE Trans. Wirel. Commun.*, vol. 21, no. 12, pp. 10 662–10 677, 2022.

[10] R. H. Y. Perdana, T.-V. Nguyen, and B. An, "A Deep Learning-Based Spectral Efficiency Maximization in Multiple Users Multiple STAR-RISs Massive MIMO-NOMA Networks," in *2023 Twelfth Int. Conf. Ubiquitous Futur. Networks*. Paris, France: IEEE, 2023, pp. 675–680.

[11] T. V. Nguyen, V. D. Nguyen, D. B. Da Costa, and B. An, "Hybrid User Pairing for Spectral and Energy Efficiencies in Multiuser MISO-NOMA Networks with SWIPT," *IEEE Trans. Commun.*, vol. 68, no. 8, pp. 4874–4890, Aug. 2020.

[12] F. Fang, B. Wu, S. Fu, Z. Ding, and X. Wang, "Energy-Efficient Design of STAR-RIS Aided MIMO-NOMA Networks," *IEEE Trans. Commun.*, vol. 71, no. 1, pp. 498–511, 2023.

[13] V. D. Nguyen, H. V. Nguyen, O. A. Dobre, and O. S. Shin, "A New Design Paradigm for Secure Full-Duplex Multiuser Systems," *IEEE J. Sel. Areas Commun.*, vol. 36, no. 7, pp. 1480–1498, 2018.

[14] R. H. Y. Perdana, T.-V. Nguyen, and B. An, "Deep Learning-based Power Allocation in Massive MIMO Systems with SLNR and SINR Criterions," in *2021 Twelfth Int. Conf. Ubiquitous Futur. Networks*. Jeju Island, Republic of Korea: IEEE, 2021, pp. 87–92.