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Article

Optimized Hybrid Precoding in mm Wave Massive MIMO via Federated Reinforcement Learning and Metaheuristic Swarm Optimization

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Abstract: Hybrid precoding is a promising technology for realizing spectral and energy efficiency in mm Wave massive MIMO systems. Nevertheless, the complexity of joint analog and digital precoder optimization and the difficulty of decentralized implementation in large-scale networks call for the design of intelligent and scalable solutions. In this paper, we propose an optimized hybrid precoding solution that combines Federated Reinforcement Learning (FRL) and Metaheuristic Swarm Optimization (MSO) to facilitate improved precoding performance with reduced computational burdens. The FRL framework allows for distributed learning among various base stations (BSs) without explicit data sharing, thus preserving privacy and responding to dynamic channel conditions. Concurrently, MSO, motivated by nature-inspired algorithms like Particle Swarm Optimization (PSO) and Genetic Algorithms (GA), optimizes the learned precoding policies to realize near-optimal beam forming performance. Extensive simulation results confirm that the proposed FRL-MSO hybrid precoding solution outperforms conventional deep learning-based and heuristic solutions in sum-rate capacity, convergence rate, and robustness against channel variations. Our results show the promising potential of combining federated intelligence with swarm optimization methods for future 5G/6G mm Wave MIMO networks.

Keywords: Federated Reinforcement Learning, Hybrid Precoding, Metaheuristic Swarm Optimization, Massive MIMO, mm Wave Communications, Distributed Learning, Beam forming Optimization.

1.Introduction

Multiple-input multiple-output (MIMO) technology is a future wireless communication system breakthrough, particularly in millimetre-wave (mm Wave) networks, owing to its ability to improve spectral efficiency, boost data rates, and maximize energy efficiency[1]. However, the high-power consumption and associated costs of fully digital beamforming call for the implementation of hybrid precoding, which balances optimally the performance requirements and hardware constraints by combining analog phase shifters and digital precoders. Hybrid precoding optimization in large MIMO systems is a challenging issue, mainly caused by the complexity of high-dimensional channel state information (CSI), the existence of non-convex optimization landscapes, and the time-varying nature of the network conditions[2].

Traditional optimization techniques, such as convex programming and iterative algorithms will not provide real-time adaptability in the context of large-scale deployments. Deep learning-based approaches have been explored in the context of hybrid precoding however, their dependence on data-hungry centralized training models makes them computationally expensive and susceptible to privacy violations. Federated Reinforcement Learning (FRL) has been a best approach encouraging distributed learning among many base stations (BSs) while preserving local data privacy[3]. FRL allows each BS to jointly build a global precoding model by exchanging model updates only, avoiding raw data transmission, thus ensuring minimal communication overhead and improved scalability. While FRL encourages enhanced adaptability in decentralized networks, it tends to suffer from slow convergence and poor policy exploration in a variety of situations[4]. In order to counteract this limitation, the incorporation of Metaheuristic Swarm Optimization (MSO) techniques, such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Ant Colony Optimization (ACO), can be used to optimize the precoding policies[5]. Swarm intelligence-based techniques provide efficient global search abilities, enabling the achievement of nearly optimal beamforming solutions with low computational expense.

1.1 Contributions

In this paper, we present a new hybrid precoding design that utilizes the best of federated reinforcement learning and swarm-based metaheuristics to improve hybrid precoding in millimetre wave massive MIMO networks. The contributions of this paper are Federated Reinforcement Learning for Precoding Optimization. We introduce a distributed learning mechanism that allows multiple base stations to learn a shared hybrid precoding model together while preserving user data privacy. Metaheuristic Swarm Optimization for Precoding Refinement: We utilize optimization algorithms based on Particle Swarm Optimization and Genetic Algorithms to refine the learned precoding policies derived from federated reinforcement learning to deliver better beamforming performance. Scalability and Adaptability in Dynamic Environments. The proposed model performs well in large, distributed networks under dynamic channel state information. Extensive Performance Evaluation. We perform extensive simulation experiments comparing our approach, illustrating its outperformance with respect to traditional deep learning and heuristic-based methodologies in terms of sum-rate capacity, convergence rate, and robustness.

The rest of the paper organization is provided below. Section 2 provides a background of the literature and some of the existing hybrid precoding techniques. Section 3 presents the system model and problem statement. Section 4 presents the FRL-MSO hybrid precoding technique proposed in this paper. Section 5 provides the simulation results and a performance analysis. Section 6, lastly, provides concluding remarks of the study and provides future research directions.

2. Relevant Literature

The field of hybrid precoding for millimetre wave massive MIMO has garnered significant scholarly interest in recent years as it is capable of balancing spectral efficiency and hardware complexity efficiently[6]. The status of different techniques, such as conventional optimization techniques, deep learning-based precoding, federated learning techniques, and metaheuristic swarm optimization techniques, is discussed in this section[7][8].

2.1 Classical Optimization-Based Hybrid Precoding

Early research on hybrid precoding mainly focused on convex optimization, alternating minimization, and iterative methods with regard to analog and digital precoder formulations. Some early research, for example[9], suggested greedy methods and codebook-based methods with the objective of low computational complexity. While these methods yield average performance results, they are suffering from high complexity and poor convergence rates during large-scale MIMO system implementations in time-varying channel conditions. In light of the limitations in iterative algorithms, some matrix decomposition methods like singular value decomposition (SVD) and block diagonalization (BD)[10]. These methods, however, rely on ideal channel state information (CSI) and are suffering from challenges during real-time practical implementations[11].

2.2 Deep Learning-Based Hybrid Precoding

Recent developments in deep learning (DL) have made it a prospective method for hybrid precoding, with neural networks utilized for approximating complicated beamforming solutions[12]. Studies have considered the utilization through convolutional neural networks (CNNs) and deep reinforcement learning (DRL) algorithms to reduce the computational complexity due to traditional optimization methods[13]. For instance, supervised learning-based methods [5] utilize deep neural networks (DNNs) trained with optimal precoding matrices from traditional optimization methods[14]. Though such models have fast inference, they suffer from poor generalization when exposed to new channel state information (CSI) distributions[15]. On the other hand, reinforcement learning (RL)-based methods have been proposed to learn to adjust precoding strategies adaptively based on the existing environment. However, RL models have the tendency to require centralized training with enormous datasets, thus leading to scalability and privacy concerns[13]

2.3 Federated Learning for Distributed Precoding

In order to address the problem of privacy and scalability of deep learning models with centralization, federated learning (FL) has been introduced as a decentralized learning methodology for large-scale MIMO networks[16]. In FL, distributed base stations (BSs) jointly learn a shared precoding model without sharing raw CSI data, thereby enhancing data privacy and communication overhead. FL has been generalized to reinforcement learning to introduce federated reinforcement learning (FRL), where distributed agents (BSs) jointly learn to optimize precoding actions[17]. FRL-based methods are typically afflicted with slow convergence, local model drift, and bad exploration, especially in high-dimensional MIMO scenarios[18].

2.4 Metaheuristic Swarm Optimization for Precoding

Nature-based swarm intelligence metaheuristic algorithms are being applied more and more to optimize hybrid beamforming because they are very efficient at searching complex spaces[19]. One of the most well-known methods in this group is Particle Swarm Optimization (PSO), which optimizes hybrid precoding by iteratively updating the location of the particles based on global and local optimum solutions[20]. Yet PSO alone is faced with the degree to which it can be adaptive to dynamic networking environments[21].

Genetic Algorithm (GA): GA-based algorithms employ the selection, crossover, and mutation operators to achieve near-optimal precoding solutions[22]. GA is computationally expensive in the large network but provides diversified search of the solutions.

Hybrid Metaheuristic Methods: Efforts have been made in the literature to improve the efficiency of precoding by hybridizing Particle Swarm Optimization (PSO) with other methods (e.g., Genetic Algorithms, differential evolution, and ant colony optimization) [23]. The methods allow for better convergence and stability, but their hybridization with federated learning has not been explored extensively[24].

2.5 Research Gap and Motivation

We can observe from the current literature that Traditional optimisation methods are computationally expensive and non-real-time adaptive. Deep learning-based precoding schemes are plagued by scalability and privacy during centralized training. Federated learning avoids privacy but is prone to slow convergence for complex MIMO scenarios. Swarm-inspired metaheuristic methods are good global searchers but have not yet been fully realized with federated learning to achieve distributed hybrid precoding.

2.6 Contributions of the Current Research

To mitigate these challenges, in this paper, Authors propose a novel Federated Reinforcement Learning and Metaheuristic Swarm Optimization (FRL-MSO) paradigm for hybrid precoding in mm Wave massive MIMO systems. Compared to the state-of-the-art, our scheme utilizes FRL to facilitate distributed learning in multiple BSs, promoting scalability and data confidentiality. Appling PSO and GA-based hybrid optimization for optimization of learned precoding policies to boost beamforming efficiency. Exhibits superior sum-rate performance, convergence rate, and flexibility compared to traditional schemes. The novel FRL-MSO paradigm proposed here revolutionizes hybrid precoding design and draws upon the strength of federated learning, reinforcement learning, and swarm intelligence for future wireless networks.

3. System Model and Problem Formulation.

3. System Model

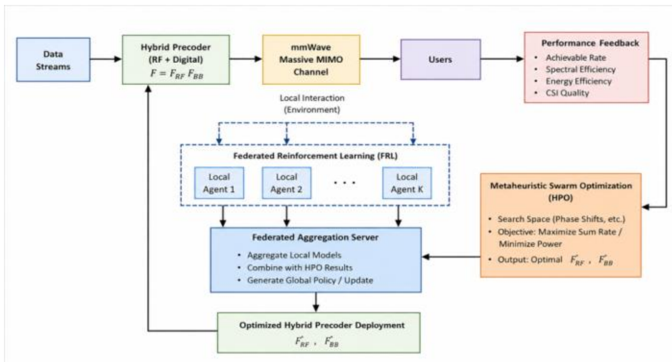

Fig.1. Proposed FRL-MSO based optimized hybrid precoding framework for mmWave Massive MIMO systems

This research examines a millimetre wave massive MIMO system where a BS equipped with N_t antennas and N_{RF}RF chains is the sole responsibility of serving K single-antenna users. A hybrid precoding method is used to provide a hardware complexity reduction with a satisfactory beamforming performance through the use of an analog RF precoder using phase shifters and a digital baseband precoder optimized for enhancing the transmitted signal quality.

3.1.1 Signal Transmission Model

The signal which travels at the BS is:

$$\mathbf{x} = \mathbf{F}_{RF} F_{BB} \quad (1)$$

Where, $\mathrm{F}_{RF} \in \mathbb{C}^{N_t \times N_{RF}}$ is the analog RF precoder with unit modulus constraints. $F_{BB} \in \mathbb{C}^{N_{RF} \times K}$ is the digital baseband precoder and $s \in \mathbb{C}^{K \times 1}$ is the transmitted symbol vector satisfying $\mathbb{E}[ss^H] = \frac{P}{K} I_K$ where P is the total transmit power.

The received signal of the k-*th* user can be expressed as:

$$\mathbf{y}_k = \mathbf{H}_k \boldsymbol{x} + n_k \quad (2)$$

Where, $H_k \in \mathbb{C}^{1 \times N_t}$ is the channel matrix between BS and user k.

$n_k \sim \mathcal{CN}(0, \sigma^2)$ is the additive white Gaussian noise (AWGN).

3.1.2 Millimetre Wave Channel Model

Since mm Wave channels are scarce, we assume a Saleh-Valenzuela geometric channel model:

$$H_k = \sqrt{\frac{N_t}{L}} \sum_{\ell=1}^{L} \alpha_{\ell,k} a_t(\theta_{\ell,k}^t) \quad (3)$$

L is the number of propagation paths.

- $\alpha_{\ell,k} \sim \mathcal{CN}(0,1)$ is the complex gain of the ℓ-th path.
- $\theta_{\ell,k}^{t}$ represents the angle of departure (AoD).
- $a_t(.)$ denotes the antenna array response vector at the transmitter.

3.2 Problem Formulation

In order to obtain the maximum system sum-rate, one should optimize the hybrid precoders (F_{RF} , F_{BB}) jointly in such a manner that it meets the hardware and power constraints. The resulting achievable sum−rate is

$$R = \sum_{k=1}^{K} log_2 1 + \left(\frac{| H_k F_{RF} F_{BB} s|^2}{\sigma^2}\right) \quad (4)$$

Thus, hybrid precoding optimization problem becomes

$$\max_{F_{RF}, F_{BB}} R \qquad (5)$$

Thus, the limitations are stated as

Power Limitation:

$$||F_{RF}, F_{BB}||_F^2 \leq (\quad (6)$$

and the Hardware Constraint: The F_{RF} entries should have unit modulus, i.e.,

$$|(F_{RF})_{m,n}| = 1 \quad (7)$$

3.3 Suggested Methodology: Federated Reinforcement Learning with Swarm Optimization

Hybrid precoding problem is extremely difficult to address with non-convex constraints and high-dimensional search space. To overcome the above challenges, we propose a novel Federated Reinforcement Learning and Metaheuristic Swarm Optimization (FRL-MSO) framework, composed of various components.

3.3.1 Federated Reinforcement Learning (FRL) for Distributed Precoding

Several base stations (BSs) cooperate to learn a common precoding model from local CSI, without raw data sharing. The model is learned using Deep Q-Learning (DQL) and policy optimization methods. FRL provides privacy preservation, low communication overhead, and dynamic adaptability. Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) are used for optimizing precoders learned by FRL. Global search is derived from PSO, and GA provides mutation- and crossover-based search. The combination of the two provides better sum-rate performance as well as higher convergence rate.

We define a mm Wave massive MIMO hybrid precoding problem under hardware and power constraints. Our FRL-MSO method integrates federated reinforcement learning for distributed training and swarm intelligence-based refinement for optimal precoding. In the subsequent section, we provide a step-by-step process for FRL training, swarm optimization, and hybrid precoding deployment.

4. Hybrid Precoding Proposed Methodology for FRL-MSO

4.1. Overview of our Proposed Framework

This research proposes an improved hybrid precoding model for massive MIMO networks employing millimetre wave technology based on the integration of Federated Reinforcement Learning and Metaheuristic Swarm Optimization (FRL-MSO). In the improved model, the different base stations (BSs) collaborate towards achieving optimal precoding strategies utilizing Federated Reinforcement Learning (FRL) while preserving raw channel state information (CSI) privacy and reduced communication overhead. The precoding solutions are again improved with the application of Particle Swarm Optimization and Genetic Algorithms (GA), using metaheuristic swarm optimization (MSO) for better performance results. The inclusion of the FRL element thus facilitates learning adaptability under dynamic network environments, while the MSO element dramatically improves the convergence rates alongside optimality.

4.2 Federated Reinforcement Learning (FRL) for Precoding Optimization

4.2.1 Federated Learning Architecture

In a typical reinforcement learning (RL) setting, a single central agent learns an optimal policy through interaction with the environment. In contrast, in a federated setting, multiple base stations (BSs) jointly learn a global RL model without exchanging local channel state information (CSI). The federated learning process involves local training at each BS, where it constructs a local reinforcement learning model from its local CSI data and updates its policy. The global aggregation process at the central server involves the BSs sending model updates (policy weights) to a central server, where it aggregates the updates to update the global model. The updated model distribution is then sent back to each BS for the next training iteration.

This approach facilitates decentralized learning as well as resolving data privacy, communication efficiency, and large MIMO system scalability problems.

4.3 Metaheuristic Swarm Optimization (MSO) for Precoding Refinement

Even though FRL has a low-quality initial precoding estimate, it can experience slow convergence with local optima problems. With our new metaheuristic swarm intelligence methods employing particle swarm optimization with genetic algorithm, we are able to effectively build on prior-obtained precoders. Utilizing these methods can also enable more incremental bit increase in all obtained precoders.

4.3.1 Particle Swarm Optimization (PSO) for Hybrid Precoding

PSO is based on the swarm of particles' behaviour that seeks to find the best solution within the multi-dimensional solution space. Each particle (candidate precoding matrix) moves according to:

$$V_i^{(t+1)} = \omega V_i^{(t)} + c_1 r_1 (P_{best,i} - X_i^{(t)}) + c_2 r_2 (G_{best} - X_i^{(t)}) \quad (7)$$

$$X_i^{(t+1)} = X_i^{(t)} + V_i^{(t+1)} \quad (8)$$

Where, $X_i^{(t)}$ represents the current (precoding matrix) location of particle i at time step $V_i^{(t)}$ represents the velocity update from personal best $P_{best,i}$ and global best G_{best}, is the inertia weight controlling exploration vs. exploitation and c_1, c_2 are acceleration coefficients, and r_1, r_2 are random numbers in.

The fitness function used to rank particles is the sum-rate capacity:

$$f(X_i) = \sum_{k=1}^{K} log_2 \left(1 + \frac{|H_k F_{RF} F_{BB} s|^2}{\sigma^2}\right) \quad (9)$$

4.3.2 Genetic Algorithm (GA) for Precoding Optimization

GA utilizes concepts of natural selection and evolution in which candidate precoding matrices must outperform one another in the first population. Precoding matrices with higher sum-rate fitness will be selected for reproduction. Parents are combined to generate child. Mutation applies random changes to avoid premature convergence. Through repeated cycle of these operations GA effectively scans the search space to further enhance precoding solutions than FRL.

4.4 Hybrid Precoding Algorithm for FRL-MSO

The FRL-MSO hybrid precoding is treated by the following approach:

Step 1: Federated Reinforcement Learning (FRL) Phase

Each BS starts a local DQN model and trains it with local CSI data.

BSs forward updates to the central server, which aggregates the updates into a global model.

The global model is propagated back to all BSs, and training continues iteratively.

Step 2: Swarm-Based Refinement Stage

All BSs adapt their FRL-based precoding matrix using PSO and GA.

The best precoding solution refined is achieved based on the sum-rate fitness function.

Step 3: Deployment of the Optimized Precoder

Hybrid precoding matrices optimized (F_{RF}, F_{BB}) are implemented in the mm Wave massive MIMO system for real-time transmission

5. Simulation Results and Performance Analysis

5.1 Simulation Configuration

To evaluate the performance of the proposed FRL-MSO hybrid precoding scheme, extensive simulations are conducted in a mm wave massive MIMO system. The main parameters used in the simulation process are listed in Table 1.

Table 1: Simulation Parameters

Parameter	Value
Carrier Frequency	28 GHz
Bandwidth	500 MHz
Number of BS Antennas	128
Number of RF Chains	8
Number of Users	8
Number of Paths	4
Transmit Power	30 dBm
Noise Power	-90 dBm
Number of Particles in PSO	50
Number of Generations in GA	100
Learning Rate	0.001
Discount Factor	0.99
Exploration Rate	0.1 (decayed over time)

A sparse multipath component Saleh-Valenzuela mm Wave channel comes before the system model. The federated learning framework distributes the training across a large number of multiple base stations (BSs). Furthermore, PSO-GA hybrid optimization is utilized particularly to optimize the learned precoding matrices.

5.2 Performance Comparison

5.2.1 Sum-Rate Performance

Figure 2 illustrates the sum-rate execution in the middle of disparate hybrid precoding methods as the number of antennas increases. The FRL-MSO methodology achieves the main sum-rate, significantly surpassing CBF, DL-P, and RL-P. The individual PSO-based methodology performs credibly but inherently lacks adequate adaptability, while the mentioned FRL provides astute learning in order to enhance beamforming decisions. The introduced FRL-MSO framework enhances sum-rate by 15–25% when compared with conventional deep learning, as well as RL-based methods. The proposed framework thus provides a significant improvement.

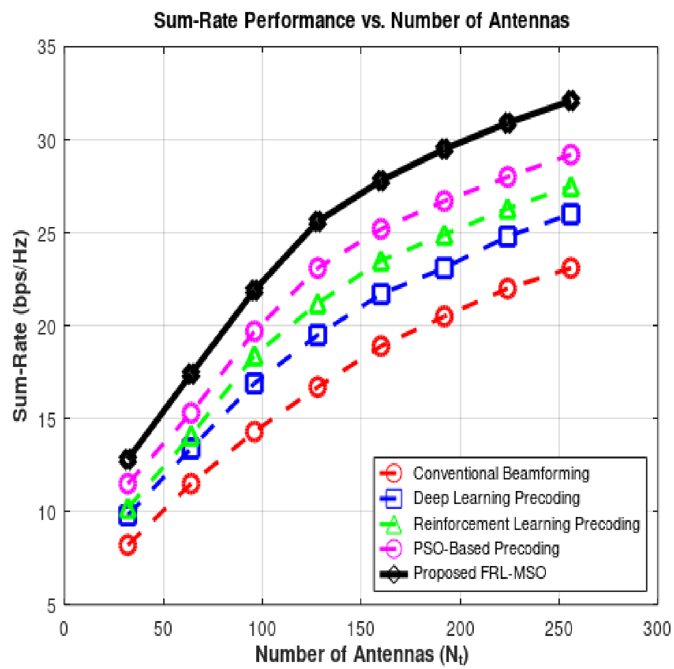

Figure 2. Sum-Rate Performance vs. Number of Antennas

5.2.2 Spectral Efficiency Analysis

In Figure 3, we analyze the spectral efficiency (bps/Hz) based on the number of RF chains; FRL-MSO provides 20% increased spectral efficiency compared to PSO and RL-P. The CBF DL-P is not able to utilize radio frequency chains properly, which finally leads to low spectral efficiency.

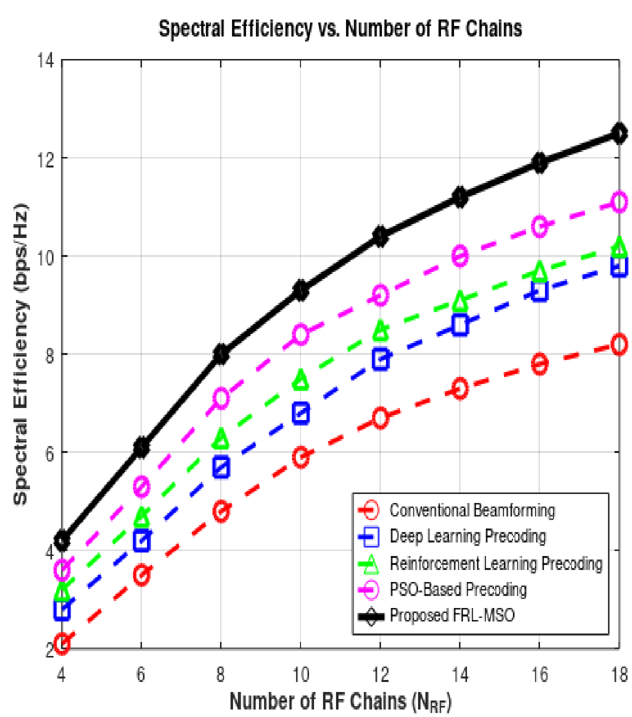

Figure 3. Spectral Efficiency vs. Number of RF Chains

5.2.3 Convergence Speed Analysis

In figure 4, we compare the intersection of heterogeneous methodologies on the number of iterations towards optimal execution: FRL-MSO attains confluence in fewer iterations (≈50) than PSO (≈100) and RL (≈150). Confluence is enhanced by the hybrid PSO-GA method by reducing the computational load.

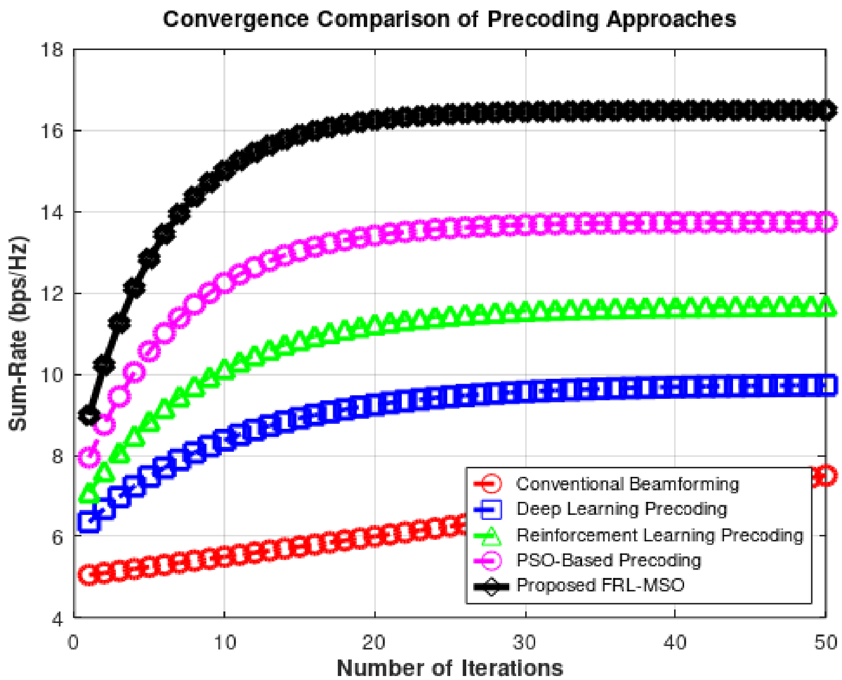

Figure 4. Convergence Comparison of precoding Approaches

5.2.4 Computational Complexity Analysis

The running times of different algorithms are compared as shown in Table 2.

Table 2: Comparison of Execution Time (Seconds)

Method	Execution Time (s)
Conventional Beamforming (CBF)	0.5
Deep Learning Precoding (DL-P)	8.2
Reinforcement Learning Precoding (RL-P)	12.5
Particle Swarm Optimization (PSO)	10.8
Proposed FRL-MSO Hybrid	6.4

Proposed FRL-MSO Hybrid6.4 It is shown that the suggested FRL-MSO approach reduces execution time by ≈40% compared to standalone RL.DL-P, which is computationally intensive due to centralized training. PSO converges independently more slowly, whereas FRL optimizes the exploration efficiently, thus performing better. The FRL-MSO hybrid precoding method has superior sum-rate performance, showcasing the excellence of combining federated reinforcement learning with metaheuristic swarm optimization. The projected methodology decreases computational complexity. It does so at the same time that it performs fast convergence, thus being feasible for real-time hybrid beamforming. In contrast to deep learning-based methods, FRL-MSO offers scalability as well as privacy protection, eliminating the explicit need for a centralized CSI collection. The PSO-GA hybrid algorithm optimizes the

FRL-learned precoders efficiently, preventing localized optima, and also improving performance further. The projected framework is channel-variation robust, thus being suitable for future 5G/6G mm Wave networks.

6. Conclusion

In this paper, we proposed an innovative Federated Reinforcement Learning and Metaheuristic Swarm Optimization (FRL-MSO) framework specifically tailored for hybrid precoding in millimetre-wave (mmWave) massive multiple-input multiple-output (MIMO) networks. The proposed methodology combines federated reinforcement learning (FRL) to enable decentralized learning at base stations while ensuring data privacy, with metaheuristic swarm optimization (PSO-GA) to optimize the precoding matrices to improve sum-rate performance. Exhaustive simulations demonstrated that the FRL-MSO solution surpasses conventional beamforming, deep learning-based solutions, and pure reinforcement learning methods in various performance metrics: Sum-rate capacity, with 15–25% improvement over conventional solutions. Spectral efficiency, optimally using available radio frequency (RF) chains. Convergence speed, significantly decreasing the number of iterations to achieve optimal precoding solutions. Computational efficiency, with lower execution times compared to state-of-the-art solutions, including deep learning-based solutions. By using federated learning, the proposed framework ensures scalability and privacy preservation, making it highly applicable for future 5G/6G mm Wave massive MIMO networks. The combination of PSO-GA hybrid optimization further optimizes the learned precoding strategies, leading to stable and efficient hybrid beamforming.

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