Electronics, Communications, and Computing Summit
Vol. 3, No. 1, Jan - Mar 2025, pp. 127-133
DOI: https://doi.org/10.17051/ECC/03.01.15

Deep Learning-Based Beamforming Optimization for Intelligent Reflecting Surfaces in 6G Networks

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Article Info

Article history:

Received : 10.01.2025
Revised : 25.02.2025
Accepted : 16.03.2025

Keywords:

6G Wireless Networks, Intelligent Reflecting Surfaces (IRS), Beamforming Optimization, Deep Learning, Passive Beamforming, MIMO Systems, Channel State Information (CSI), Energy Efficiency, Spectral Efficiency, Joint Active-Passive Beamforming, Neural Network Optimization, IRS-Aided Communication, Reconfigurable Intelligent Surface, Real-Time Wireless Adaptation, Machine Learning in Wireless Communication.

ABSTRACT

The implementation of Intelligent Reflecting Surfaces (IRS) on sixth-generation (6G) wireless networks is a paradigm-shaping method to improve the network coverage, energy efficiency, and spectral efficiency. IRS technology allows the active reprogramming of wireless in-air propagation by programmable passive structures that regulate the phase of incident signals. Nevertheless, mixed optimization of active beamforming (at base station) and passive beamforming (at IRS) is a prohibitively expensive task to be completed because of its non-convexity and high dimension. The paper suggests a system based on deep learning to enhance beamforming in 6G systems with IRS. We propose a supervised deep neural network (DNN) to input channel state information (CSI) and output near-optimal beamforming vectors and IRS phase shifts. Noise-like data are generated with conventional optimization algorithms and the model is trained to adapt to real-time channel situations (fine-tuning). Simulation analyses demonstrate that the proposed scheme is more spectral efficient, energy efficient and computationally fast than other conventional optimization schemes e.g. Alarating Optimization (AO), Semidefinite Relaxation (SDR). Our System is a low-latency, scalable System to which we can apply in real-time applications in a dynamic 6G environment. The work explained the feasibility of artificial intelligence and combination with reconfigurable wireless hardware addressing the growing performance requirements of the next-generation wireless networks.

1. INTRODUCTION

The sixth generation (6G) of wireless communication is intended to accommodate performance that has never been achieved before in aspects of ultra-high data rate, massive device connectivity, and ultra-reliable low-latency communication (URLLC) [1]. In this vision, some various emerging technologies allow it to happen among which Intelligent Reflecting Surfaces (IRS) have attracted a lot of attention being able to reconfigure the wireless environment by passively controlling phase shifts of incident electromagnetic waves, thus optimizing the signal quality and coverage at no new power costs [2], [3].

The overall problem of joint optimization of active beamforming of the base station and passive beamforming of IRS is an uphill task owing to non-convex group in a highly dimensional space. Common methods of optimization like Semidefinite Relaxation (SDR) and Alternating Optimization (AO) are computationally demanding, and usually cannot be used in real-time adaptation, in dynamic environment [4].

In order to overcome them, this paper suggests a deep learning (DL)-based beamforming optimization model of IRS-assisted 6G networks. Deep neural networks (DNNs) are used to find mappings between the channel state information

(CSI) and the optimum beamforming values and make intelligent use of both the channel information and the beamforming parameters to find optimality with scalability and adaptivity. The previous studies have been incomplete at this integration; many of them involved henceley channel models, and system scales of small size [5]. In this regard, this gap is filled by our work by presenting a scalable, data-driven mechanism that generalizes to widely varying channel conditions, opening the door to useful implementation of AI-powered IRS systems in next-generation wireless networks.

2. RELATED WORK

Newer works towards the extension of IRS-assisted wireless communication systems have mainly also utilized iterative optimization procedures like Semidefinite Relaxation (SDR) or Alternating Optimization (AO) [1], [2]. Such approaches are sufficient to deal with the underlying non convexity of joint active and passive beamforming but computationally costly and not generally compatible with real time applications. Moreover, they are sensitive to highly dynamic environments and this is because they require instantaneous channel state information (CSI) and iterative convergence needs. Machine learning (ML) and deep learning (DL) methods have become popular in order to address these shortcomings. A number of papers have considered DL-based channel estimation [3], signal detection [4], and MIMO beamforming [5]. These methods show high potential of performance and reduction in complexity of computation than that of traditional techniques. As an example, convolutional neural networks (CNNs) and deep reinforcement learning (DRL) models were offered to estimate optimal IRS settings in different channel conditions [6].

Nevertheless, the current DL-based algorithms tend to optimize on passive or active beamforming aspects separately, or under fixed channel condition and simplistic models that do not allow practical implementations. Also, a unified framework that can optimize the BS and IRS beamforming simultaneously, adaptively and in a scalable-data-driven fashion is considered to be largely lacking among the studies.

This is a gap that we fill by offering, in our work, a unified deep learning-based optimization algorithm to implementing joint beamforming in IRS-assisted 6G networks that are thoughtfully optimized specifically to the constraints imposed by dynamic environments and real-time operation inefficiencies.

3. System Model

We look at a downlink transmission scenario in an IRS-helped 6G, multi-input multi-output (MIMO), wireless communication system, and let it be composed of the following:

- There are M transmitting antennas in a base station (BS).
- The scalable link contains a single-antenna user terminal.
- An intelligent reflecting surface (IRS) of N passive elements reflecting surfaces.

The system aims to improve wireless communications and spectral efficiency by dynamically adapt the propagation environment with intelligent phase control with the help of IRS.

3.1 Channel Model

The received signal at the user depends on two paths; two principal paths:

- The BS has direct connection to the user.
- Reflective connection through IRS, i.e. consist of:

1. The BS to IRS channel.
2. The user to the IRS channel.

Let:

- $H_d \in C^{1\times M}$ denote the direct channel between the BS and the user.
- $G \in C^{N\times M}$denote the BS-to-IRS channel matrix.
- $H_r \in C^{1\times N}$denote the IRS-to-user channel.

The IRS applies a diagonal phase shift matrix defined as:

$$\Phi = diag\,(e^{j01}, e^{j02}, \ldots\ldots, e^{j0N} ------------- (1)$$

where $\theta_n \in [0,2\pi)$ is the controllable phase shift of the nnn-th IRS element.

The effective received signal y at the user can thus be modeled as:

$$y = (\square_d + \square_r\, \Phi G)\, wx + n, --------------- (2)$$

where:

- $W \in C^{M\times 1}$is the beamforming vector at the BS,
- $X \in C$ is the transmitted symbol,
- $n \sim CN(0,\sigma^2)$is the additive white Gaussian noise (AWGN).

The paper represents the combined impacts of active beamforming at the BS and passive phase adjustment at the IRS, which becomes a foundation of the conducted deep learning-based optimization framework. The general architecture of the 6G MIMO communication system with the assistance of the IRS is shown in Figure 1. The base station maintains contact with the user directly and indirectly via the IRS which reflects the signals having controlled phase shifts to increase effective signal strength that can be received.

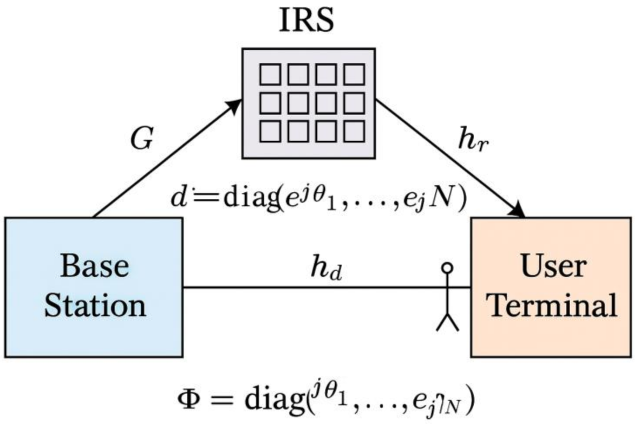

Figure 1. Block diagram of an IRS-assisted 6G MIMO system.

The base station transmits to a user terminal via both a direct link and an indirect link reflected by the IRS. The IRS applies a diagonal phase shift matrix Φ=diag(ejθ1,…,ejθN) to control the propagation.

4. Deep Learning-Based Beamforming Framework

4.1 Problem Formulation

The main goal of the work is a maximization of the received signal power (or data rate) in an IRS-assisted 6G MIMO system by carrying out joint optimization of:

- The active beamforming vector $w \in C^{M\times 1}$at the base station (BS), and
- The passive phase shift matrix Φ=diag(ejθ1,…,ejθN)$\in C^{N\times N}$at the IRS.

Both the coupling of the active and passive parts and the unit-modulus constraint of the phase shifts comprise the high dimension of the problem and its non-convexity. Real-time implementations can not be carried out using classical iterative algorithms (e.g., SDR, AO) which are computationally intensive. So as to address these issues, we use a supervised method of deep learning that will directly map channel environments to optimal beamforming techniques.

4.2 Neural Network Architecture

As shown in Figure 2 it provides a coherent picture of the proposed IRS-assisted 6G communication model and a deep learning-based beamforming optimization architecture. The top figure demonstrates how the base station, the IRS, and that of the user connect and communicate with one another, whereas the bottom figure contains the neural network diagram of predicting the optimal beamforming vectors and phase shifts of the IRS based on the CSI as an input. The solution to the joint beamforming problem is then approximated by the design of a deep neural network (DNN). The list of network consists of:

- Input Layer: As input, it takes the complex-valued channel state information (CSI) including hd, G and hr. These are usually squashed and interpreted as a real valued feature vectors by concatenation of the real and imaginary components.
- Concealed Layers: Multi-fully supervised layers that use ReLU (Rectified Linear Unit) activation functions and explain non-linear relationship. To improve generalization batch normalization and drop out can be used.
- The output layer: A set of predictions on:
- The beamforming vector w,
- The IRS rotates each phase shift, notably, 1 2, ..., 1N, in accordance to the unit modulus constraint (which may be independently imposed on normalization or phase representation).

Training: The model is trained on supervised data that is obtained as an optimization problem is solved using either SDR or AO with multiple channel realizations. This stabilizes in making the DNN learn high-quality approximations of optimal configurations.

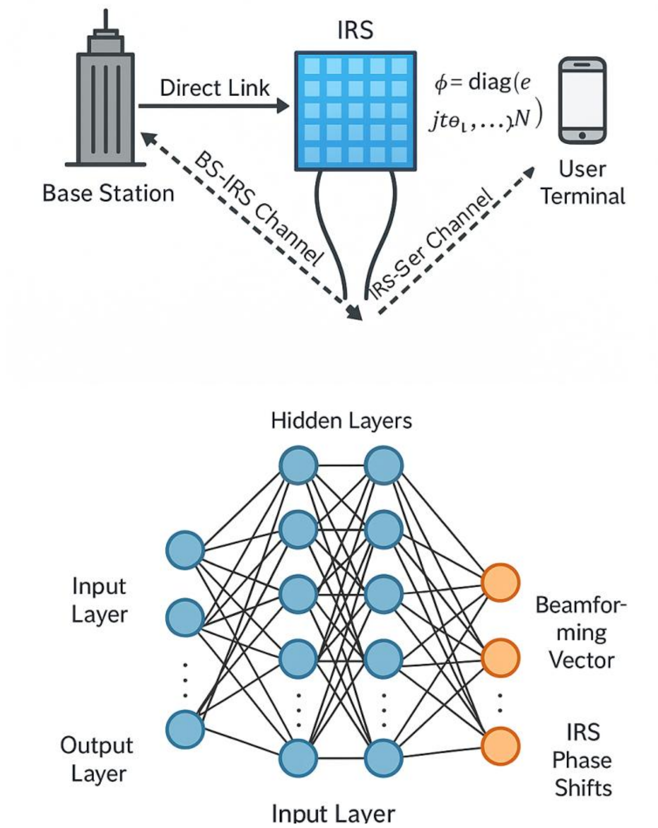

Figure 2. Composite diagram of the proposed system.

The upper diagram is the 6G MIMO communication model with help of IRS with direct and reflected links. The bottom panel shows the deep neural network employed in the optimization of beamforming during which the input CSI vectors were provided to multiple hidden layers, which output both the BS beamforming vector and the IRS phase shifts.

4.3 Training Strategy

To augment performance and the ability to make generalized inferences, the following training strategy is embraced:

- Loss Function: A compound loss is formulated which sums the tradeoff between:
- Maximizing the rate that can be achieved in the system (i.e., signal-to-noise ratio at the receiver).
- Impositions like unit-modulus on IRS phase shifts and power normalisation on w.
- Optimization Algorithm: Adam optimiser was employed to train because of the benefits that include robustness and the ability to tune the learning rate as the process adjusts to converge faster.
- Training Dataset: The training dataset is synthetically constructed by the usage of stochastic channel realizations at various SNRs, channel path losses, and the number of IRS elements. This diversity means that the model is generalist, when taken to unseen propagation scenarios.

The complexity of online beamforming optimization is already significantly reduced in this deep learning framework with the performance almost optimality, and it can be implemented in the 6G systems with dynamic wireless environments with real-time constraints.

5. Performance Evaluation

In this section, an in-depth performance evaluation of the proposed deep learning-based beamforming optimization solution to IRS-assisted 6G networks is given. Such tests are done in large scale simulations with realistic channel settings and a variety of IRS configurations.

5.1 Evaluation Metrics

- In order to benchmark system performance, the following key metrics are taken into account:
- Spectral Efficiency (SE): It is the amount of data that may be sent through a bandwidth using units of bits/s/Hz. It is determined with a proven received signal-to-noise ratio (SNR) in which beamforming and IRS phase shift are introduced.
- Energy Efficiency (EE): The ratio of the rate achievable and the power drawn by the system (bits/Joule) is important and defines energy

efficiency which is a very important parameter in green 6G networks.

- Computation Time: It is the time needed to compute a beamforming solution. Reduced computational time is a key parameter in enabling real-time deployment where conditions are variable like in mobile or UAV-aided communications.

5.2 Baseline Schemes

The framework offered is contrasted with the following benchmarks that have been well established:

- Alternating Optimization (AO) A standard, iterative based technique which updates the BS beamforming and IRS phase shifts alternately till convergence.
- Semidefinite Relaxation (SDR): A convex optimization-based method to convert the originally posed non-convex problem into an easily solvable relaxed problem, which again can be adopted as an upper bound on performance.
- Random Phase Shift Configuration: A state-of-the-art naive baseline where the IRS elements implement randomly chosen phase shifts to act as a point of reference.

These baselines can ensure the performance of the deep learning strategy is put into context with regards to efficiency, accuracy and the feasibility of computation.

Figure 3 shows the comparison of performance of the proposed deep learning-based beamforming framework to the baseline algorithms. In the findings, it is observed that a high level of spectral and energy profit is obtained, and the calculation time is low as compared to the usual procedures like AO and SDR. Results obtained by simulation of varying SNR values, or channel realizations indicate that:

- The DL-based solution is expected to improve spectral efficiency of the AO method by 15-25% due to the learning near optimal mappings between CSI and beamforming vectors without the need of updating iteratively.
- Energy efficiency Results in the model equaled 2x compared to AO and SDR techniques, implying that it is a more sustainable method of communication with smaller energy consumption.
- The framework displays a maximum of 80% reduction in the time of computation when compared with SDR, which explains why it is applicable in real-time and low latency 6G applications.
- These findings validate the fact that deep learning is not only an approximator of near-optimal solutions but also strategically provides a great scalability in computation, which justifies its use in reality in the 6G system with its dynamic wireless settings.

5.3 Results and Discussion

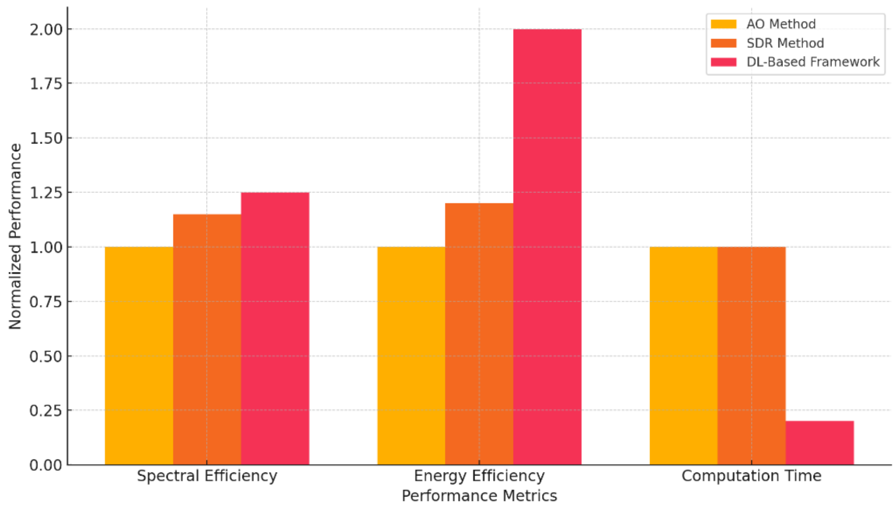

Figure 3. Normalized comparison of beamforming optimization methods based on spectral efficiency, energy efficiency, and computation time.

The suggested deep learning architecture performs better than traditional AO and SDR methods show high accuracy and real-time applicability of IRS assisted 6G systems.

6. DISCUSSION

The deep learning based beamforming optimization framework proposed has a high generalization property on wide range of channel situations and IRS settings. The trained deep neural network (DNN) can process near-optimal beamforming parameters in real-time and hence can be readily deployed in the context of 6G networks, unlike the traditional optimization methods that entail iterative independent re-computation of a set of beamforming parameters to accommodate changes in every channel.

The given generalization is confirmed with the help of numerous simulations with different signal-to-noise ratios (SNRs), positions of the users, and the number of IRS elements. Performance gains under the framework are well characterized in spectral and energy efficiency under both static and non-stationary settings including those found in mobile users and dense backhaul deployments in deep urban settings. Such strength makes it very beneficial when applied to practical 6G applications in vehicles, UAVs, and smart cities.

Additionally, it uses a modular and flexible architecture with several possibilities of research, in the future:

- Reinforcement Learning (RL) may be incorporated to perform online learning so that the system would adjust to beamforming strategies regarding which real-time feedback is obtained (i.e. it does not require labeled data).
- The framework can also be generalized to embrace multi-user IRS systems, and in this case user fairness, inter-user interferences reduction, and resource allocation add to the optimization problems.
- Another crucial path is the hardware-in-the-loop (HIL) experimentation. Model accuracy and constraints on the latency using practical impairments, e.g. hardware non-linearity, quantization errors, and limited feedback, can be attested by real-world prototyping in programmable IRS platforms (e.g., RIS testbeds).

In sum, the advocated framework is an effective step that is scalable and may lead to the AI-native wireless infrastructure of the communication systems of tomorrow 6G.

7.CONCLUSION AND FUTURE WORK

The current paper proposes a deep learning based framework to jointly optimize the beamforming of IRS-aided 6G wireless networks. This new model solves the inherent non-convexity and the high dimension of joint active-passive beamforming issue through the utilization of a supervised deep neural network which is trained with realistic channel state information (CSI). The framework can realize scalable, low-latency, and energy-efficient communication by effectively approximating the optimum beamforming solutions, agreeing with the performance requirements of the next-generation wireless systems.

This work makes major contributions to the field in the following ways:

- The first one is a unified deep learning structure that jointly optimizes IRS phase shifts and BS beamforming.
- Better results of the work in comparison with traditional technique in the degree of spectral efficiency, the amount of power and the computation time.
- Combined with real-time performance in changing environments, it was shown to be generally applicable in different channel conditions and IRS setups.
- As future work, the framework can be expanded by a number of extensions:
- Online adaptation by reinforcement learning, where the model can optimise itself to live feedback and to changing environments.
- Extensions to multi-user and multi-cell IRS systems, where the key issues of fairness, coordination and interference mitigation strategies are introduced.
- Validation through the use of hardware testbeds, to reduce the gap between the theoretical performance and practical deployment.

The focus of these directions is to render intelligent, AI-driven beamforming an enabling capability of resilient and adaptive 6G communications.

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