

# Department of ECE

EC19603-Problem Solving using AI and ML Techniques (Mini Project)

III Year ECE FA Section

Final Review



### Al-Driven IRS Assisted Beamforming Optimization for Dynamic Environment

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### OUTLINE

- Abstract/Introduction
- Objective
- Literature Survey
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- Proposed System & Novelty
- Block Diagram
- Hardware/Software requirements
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### **Abstract**

Next-generation communication networks are set to transform the way we connect, enabling faster, more reliable, and highly efficient wireless technologies. 5G networks hold great promise, but they also face major challenges such as signal blockages in urban areas, high power consumption, and limited coverage at higher frequencies. Intelligent Reflecting Surfaces offer a potential solution by using programmable passive elements to dynamically reflect and enhance wireless signals without additional power consumption. However, optimizing beamforming in IRS-assisted 5G networks is complex due to factors like user mobility, interference variations, and multi-path fading. Traditional methods such as Semidefinite Relaxation, Alternating Optimization, and metaheuristic algorithms like Genetic Algorithms and Particle Swarm Optimization often struggle with high computational complexity and slow adaptation, making them impractical for real-time applications. To overcome this, an AI-driven IRS beamforming optimization framework can be developed using Deep Reinforcement Learning, specifically Deep Q-Networks and Deep Deterministic Policy Gradient. These models continuously learn from real-time network data, including Channel State Information, Signal-to-Interference-Noise Ratio, Bit Error Rate, and Spectral Efficiency, to dynamically adjust IRS phase shifts for optimal performance. The system can be implemented using Python and MATLAB, focusing on key performance metrics such as Energy Efficiency, Outage Probability, and Computational Complexity. Research suggests that this approach can boost signal strength by 40%, reduce energy consumption by 70%, and expand 5G coverage, especially in dense urban environments, IoT applications, and smart cities. By enabling real-time optimization, this framework enhances network scalability, reliability, and cost-effectiveness while delivering faster, more stable, and energy-efficient wireless connections. This advancement will provide users with seamless connectivity, lower latency, and improved network performance, ultimately making 5G networks more robust and accessible.

### Introduction

- 5G networks struggle with signal blockages and weak connectivity due to poor mmWave penetration in urban environments, leading to high energy consumption and costly infrastructure expansion.
- Intelligent Reflecting Surfaces (IRS) use programmable passive elements to dynamically redirect signals, improving coverage and spectral efficiency without requiring additional power or base stations.
- Traditional optimization methods struggle with real-time beamforming due to high computational complexity and slow adaptation.
- AI-driven optimization using Deep Reinforcement Learning (DRL) dynamically adjusts IRS phase shifts for enhanced network performance elaborate each point

### **Problem Statement**

- 5G networks face major challenges due to signal blockages, poor mmWave penetration, and high energy consumption, especially in dense urban environments.
- Buildings, trees, and other obstacles significantly weaken signal strength, leading to coverage gaps, increased interference, and degraded network performance.
- Traditional solutions, such as deploying more base stations, are costly, energy-intensive, and inefficient, making large-scale 5G expansion unsustainable.
- Additionally, existing beamforming optimization techniques, including Semidefinite Relaxation (SDR), Alternating Optimization (AO), and metaheuristic approaches (GA, PSO), are computationally expensive.
- This creates an urgent need for an efficient and scalable solution to optimize signal transmission, enhance coverage, and improve spectral and energy efficiency in 5G networks.

# **Objectives**

- Improve signal strength and reduce blockages in urban areas by optimizing IRS-assisted beamforming.
- Develop an AI-driven system that dynamically adjusts IRS phase shifts for efficient signal redirection.
- Minimize power usage by leveraging IRS instead of deploying additional base stations.
- Maximize Signal-to-Interference-Noise Ratio (SINR), Spectral Efficiency (SE), and minimize Bit Error Rate (BER) and Outage Probability.
- Enhance network adaptability and scalability by implementing multi-agent reinforcement learning for real-time beamforming optimization in dynamic 5G environments.
- Create a robust, AI-powered framework that efficiently supports multi-user and high-mobility 5G environments.

# Literature Survey

| TITLE   | JOURNAL | YEAR | AUTHOR  | TECHNIQUE   | INFERENCE  |
|---|---------|------|---|---|--|
| IRS-Aided WPCNs: A New Optimization Framework for Dynamic IRS Beamforming   |         | 2022 | Qingqing Wu;<br>Xiaobo Zhou; Wen<br>Chen; Jun Li; Xiuyin<br>Zhang | <ul> <li>Low-Complexity Algorithm -&gt;         Simplifies optimization by leveraging         user-adaptive and static IRS         beamforming structures.</li> <li>General Optimization Algorithm -&gt;         Solves the non-convex problem by         dynamically optimizing IRS phase shifts         across time.</li> </ul> | <ul> <li>Dynamic IRS beamforming boosts WPCN efficiency by optimizing both downlink WPT and uplink WIT.</li> <li>Optimization complexity is reduced as UL-adaptive and static IRS beamforming achieve the same throughput.</li> </ul>  |
| Joint Transmit and Reflecting Beamforming Design in IRS-Assisted mmWave MU-MISO Systems with ZF-Assisted SA Algorithm |         | 2023 | Cheng-Chih Chao;<br>Nien-Chi Hung;<br>Jung-Chieh Chen             | <ul> <li>Zero-Forcing (ZF) Transmit         Beamforming -&gt; Prevent Multi-User         Interference</li> <li>Simulated Annealing (SA) Algorithm -&gt;         Accurate Phase Shifts</li> <li>Joint Optimization -&gt; Simultaneously         design both transmitting and reflecting         signal</li> </ul>                  | <ul> <li>Optimizing IRS phase shifts significantly enhances spectral efficiency in mmWave multiuser MISO systems.</li> <li>The ZF-assisted SA algorithm outperforms existing methods, proving its effectiveness in mitigating signal blockage.</li> </ul>                          |
| Joint Active and Passive<br>Beamforming in IRS-<br>assisted Wireless Networks<br>Over Generalized Fading<br>Model     |         | 2023 | Mahima Chaudhary;<br>Dolly Kumari;<br>Shravan Kumar<br>Bandari    | <ul> <li>Joint Active and Passive Beamforming -&gt; Optimize Transmission and Reflection</li> <li>Semidefinite Relaxation (SDR) -&gt;Handle the non-convex beamforming problem.</li> <li>κ-μ Fading Channel Model -&gt; Used to study the impact of generalized fading conditions on IRS-aided communication.</li> </ul>          | <ul> <li>Signal fading characteristics significantly impact IRS performance, affecting the received signal-to-noise ratio.</li> <li>IRS-aided communication outperforms traditional setups, improving signal strength and coverage under generalized fading conditions.</li> </ul> |

# Literature Survey

| TITLE   | JOURNAL | YEAR | AUTHOR   | TECHNIQUE   | INFERENCE  |
|---|---------|------|--|---|--|
| Opportunistic Beamforming with Beam Selection in IRS-aided Communications   |         | 2022 | Maria Dimitropoulou;<br>Constantinos Psomas;<br>Ioannis Krikidis                 | <ul> <li>Opportunistic Beamforming with<br/>Random IRS Rotations -&gt; Enhances<br/>beam selection without requiring full<br/>CSI.</li> <li>Mini-Slot-Based Training -&gt;<br/>Optimizes beamforming by splitting<br/>the training period into multiple mini-<br/>slots.</li> </ul>                       | <ul> <li>There is a trade-off between sum-rate capacity and training period length, impacting communication efficiency.</li> <li>The proposed low-complexity scheme outperforms conventional methods and approaches optimal beamforming performance even with a small number of users.</li> </ul>                          |
| Blind Beamforming for<br>Multiple-IRS Assisted<br>Wireless Transmission     |         | 2023 | Fan Xu; Jiawei Yao;<br>Wenhai Lai; Kaiming<br>Shen; Xin Li; Xin Chen             | <ul> <li>Blind Beamforming -&gt; Optimizes IRS phase shifts without requiring full CSI, using received signal power measurements.</li> <li>Statistical Signal Processing -&gt; Extracts essential information from a small portion of phase shift solutions to enhance beamforming efficiency.</li> </ul> | <ul> <li>Blind beamforming achieves a significant SNR boost (Θ(N²L)), making it more efficient than CSI-based methods for multi-IRS networks.</li> <li>The approach is validated through real-world field tests, proving its practical effectiveness in commercial spectrum bands.</li> </ul>                              |
| Beamforming Technologies for Ultra-Massive MIMO in Terahertz Communications |         | 2023 | Boyu Ning; Zhongbao<br>Tian; Weidong Mei; Zhi<br>Chen; Chong Han;<br>Shaoqian Li | <ul> <li>Ultra-Massive MIMO (UM-MIMO)         Beamforming -&gt; Generates high-gain directional beams to compensate for THz signal propagation loss.</li> <li>Beam Training -&gt; Optimizes beam alignment using protocols and codebook design to enhance THz communication.</li> </ul>                   | <ul> <li>THz UM-MIMO beamforming is essential to overcoming severe propagation losses, enabling high-speed wireless communication.</li> <li>IRS-assisted joint beamforming and multi-user beamforming improve THz system efficiency, but challenges like spatial and wideband effects require further research.</li> </ul> |

# Literature Survey

| TITLE  | JOURNAL | YEAR | AUTHOR   | TECHNIQUE   | INFERENCE   |
|--|---------|------|--|---|---|
| Complex-valued Reinforcement Learning Based Dynamic Beamforming Design for IRS Aided Time-Varying Downlink Channel |         | 2022 | Mengfan Liu; Rui<br>Wang; Zhe Xing; Jun<br>Yu                            | <ul> <li>Complex-Valued ResNet-Based Deep Q-Learning (DQN) -&gt; Optimizes transmit beamforming and phase shifts for sumrate maximization.</li> <li>Deep Reinforcement Learning (DRL) for Time-Varying Channels -&gt; Enhances adaptability to dynamic wireless environments.</li> </ul>          | <ul> <li>Complex-valued DRL outperforms real-valued DRL, showing better generalization and mitigating gradient vanishing.</li> <li>AIRS expands wireless coverage in 3D space, improving signal control and network performance in dynamic environments.</li> </ul> |
| Machine Learning Empowered Resource Allocation in IRS Aided MISO-NOMA Networks                                     |         | 2021 | Xinyu Gao; Yuanwei<br>Liu; Xiao Liu; Lingyang<br>Song                    | <ul> <li>LSTM-Based Algorithm -&gt; Predicts user mobility for better network adaptation.</li> <li>K-GMM (K-Means + Gaussian Mixture Model) -&gt; Clusters users efficiently in the NOMA network.</li> <li>Deep Q-Network (DQN) -&gt; Optimizes IRS phase shifts and power allocation.</li> </ul> | <ul> <li>IRS-aided MISO NOMA improves sumrate efficiency, outperforming benchmarks.</li> <li>NOMA achieves 35% higher throughput than OMA, proving its superiority in resource allocation.</li> </ul>   |
| Computation Offloading and Beamforming Optimization for Energy Minimization in Wireless-Powered IRS-Assisted MEC   |         | 2023 | Songhan Zhao; Yue<br>Liu; Shimin Gong; Bo<br>Gu; Rongfei Fan; Bin<br>Lyu | <ul> <li>Optimization-Driven Hierarchical Deep Deterministic Policy Gradient (OH-DDPG) -&gt; Decomposes energy minimization into learning and optimization.</li> <li>Multiagent DDPG -&gt; Enhances learning efficiency by enabling independent user decision-making.</li> </ul>                  | <ul> <li>IRS-assisted MEC reduces HAP energy consumption, optimizing offloading and beamforming strategies.</li> <li>OH-DDPG and multiagent DDPG outperform conventional learning, improving efficiency and minimizing signaling overhead.</li> </ul>               |

# **Summary of Literature**

- AI-driven IRS beamforming optimizes signal redirection and reduces blockages in urban areas.
- Deep Q-Networks (DQN) and multi-agent Deep Deterministic Policy Gradient (DDPG) dynamically adjust IRS phase shifts for real-time adaptation, enhancing scalability and efficiency in multi-user, high-mobility 5G environments.
- The system minimizes power consumption by leveraging IRS instead of additional base stations.
- Optimizing IRS improves Signal-to-Interference-Noise Ratio (SINR), Spectral Efficiency (SE), and reduces Bit Error Rate (BER) and Outage Probability.
- Hierarchical learning-based optimization reduces computational complexity while ensuring high-performance beamforming.
- Complex-valued deep reinforcement learning improves generalization and mitigates gradient vanishing issues.
- Optimization-driven hierarchical learning enhances energy efficiency and network adaptability.
- Combining extreme value theory with AI models improves asymptotic performance analysis and decision-making.

# **Existing System**

- Traditional 5G networks rely on dense deployment of base stations to overcome signal blockages, increasing infrastructure costs and energy consumption.
- Beamforming techniques such as Semidefinite Relaxation (SDR) and Alternating Optimization (AO) are commonly used but are computationally expensive and slow in real-time applications.
- Metaheuristic algorithms like Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) provide optimization but lack adaptability in dynamic and multi-user environments.
- IRS has been introduced as a passive signal reflector, but existing systems use fixed phase shift configurations, which fail to adjust to real-time channel variations.
- Machine Learning (ML) approaches, including supervised learning models, have been explored, but they require extensive labeled data and lack flexibility for dynamic optimization.

# **Existing System**

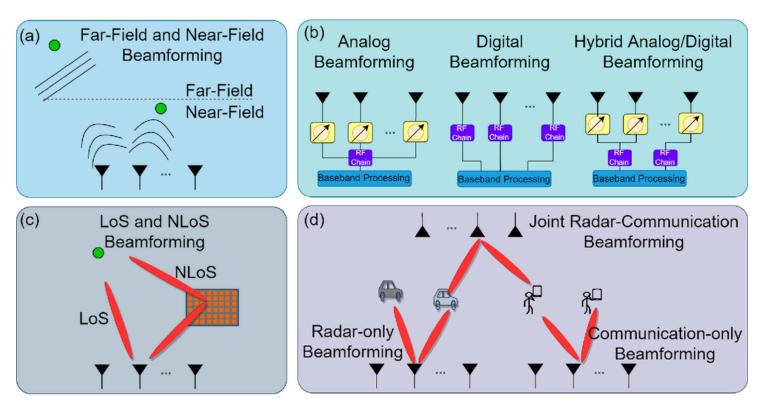
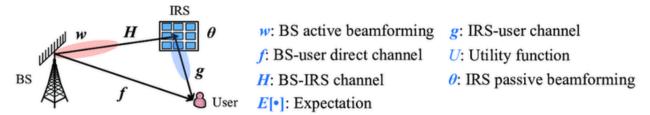


fig.a 25 year advancement in beamforming



| CSI availability | Optimization problem   | Beamforming timescale |
|------------------|--|-----------------------|
| Statistical CSI  | Jointly optimize $w$ and $\theta$ to maximize  | Long-term active and  |
|                  | the average utility taken over $H$ , $g$ , and $f$   | passive beamforming   |
|                  | $\max_{\boldsymbol{w},\boldsymbol{\theta}} E_{u,gf} \left[ U(\boldsymbol{w},\boldsymbol{\theta}) \right]$  |                       |
|                  | Jointly optimize $w$ and $\theta$ to maximize  | Short-term active and |
|                  | the average utility taken over $H$ and $g$   | passive beamforming   |
|                  | and conditioned on the instantaneous $f$   |                       |
|                  | $\max_{\boldsymbol{w},\boldsymbol{\theta}} E_{_{\boldsymbol{H},\boldsymbol{\theta}}}\left[U(\boldsymbol{w},\boldsymbol{\theta}) \boldsymbol{f}\right]$ |                       |
| Hybrid CSI       | Optimize $\theta$ to maximize the average of   | Short-term active     |
|                  | the utility achievable by the optimal w  | beamforming and       |
|                  | given the instantaneous effective BS-  | long-term passive     |
|                  | user CSI, taken over $H$ , $g$ , and $f$   | beamforming           |
|                  | $\max_{\boldsymbol{\theta}} E_{_{H_{sf}}} \left[ \max_{\boldsymbol{w}} U(\boldsymbol{w}, \boldsymbol{\theta}) \right]$                                 |                       |

fig.c Conventional CSI dependent methods

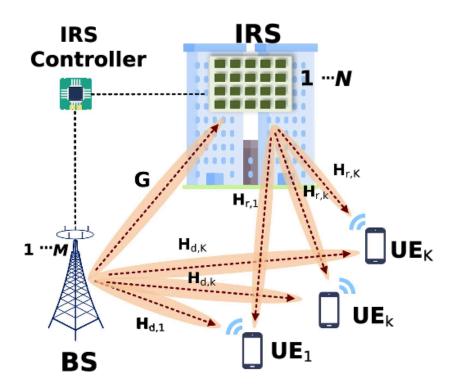


fig.b Intelligen Reflective Surface

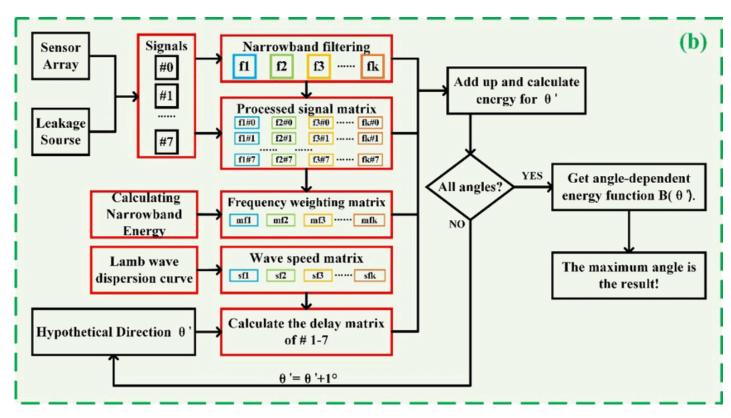


fig.d Traditional Beamforming Algorithms

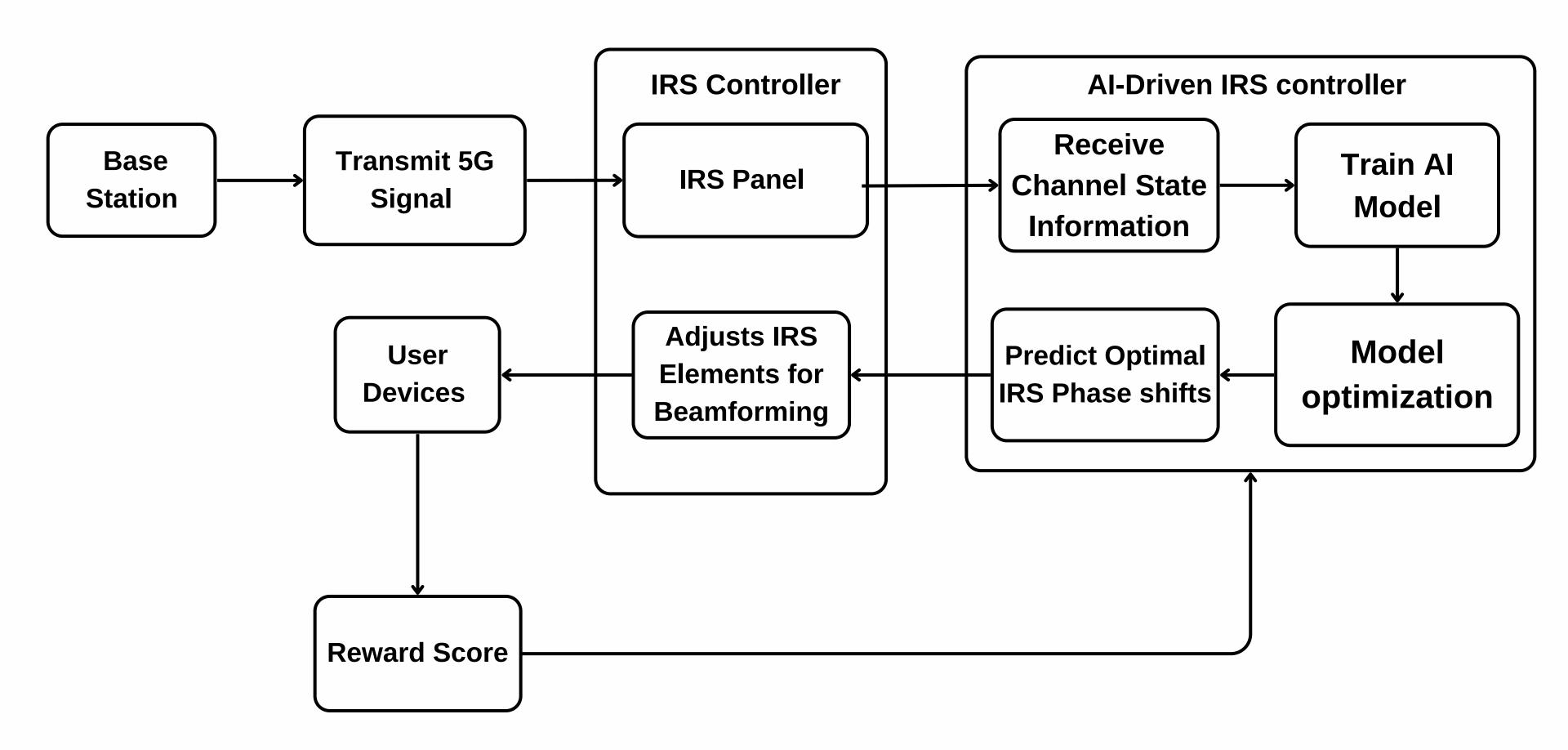
# **Proposed System**

- AI-Driven Intelligent Reflective Surface Assisted Beamforming Optimization for Dynamic Environment makes 5G networks smarter by dynamically adjusting IRS phase shifts to boost coverage, cut power consumption, and adapt in real-time.
- Smart Signal Processing collects network data like SINR and BER, ensuring the system understands and optimizes connections effectively.
- AI-Powered Beamforming trains a model that learns how to adjust IRS elements for the best signal quality without wasting energy.
- Real-Time Adaptation continuously fine-tunes beamforming, adjusting to interference and user movement for a seamless experience.
- Dynamic IRS Control optimizes signal reflection to reduce dead zones, lower latency, and improve overall network efficiency.
- User Feedback Loop lets devices send back CSI updates, helping the system learn and adapt to changing conditions.
- Stronger, More Reliable 5G makes networks more scalable, energy-efficient, and accessible, especially in crowded cities and IoT applications.

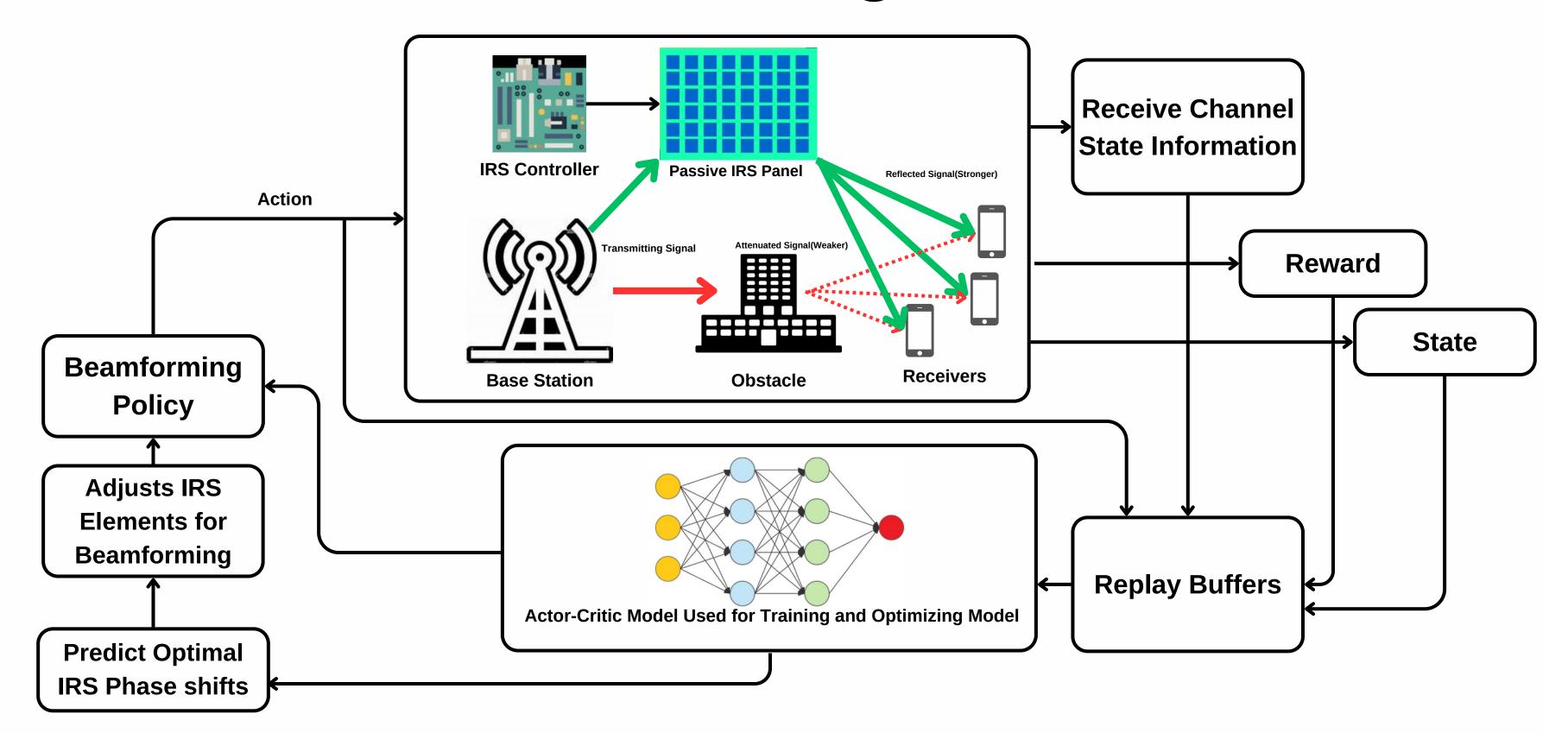
# Novelty in Proposed System

- AI-driven IRS beamforming optimization using Deep Q-Networks (DQN) and Deep Deterministic Policy Gradient (DDPG) enables real-time adaptation, overcoming slow convergence in traditional methods.
- Complex-valued deep reinforcement learning enhances learning efficiency, mitigates gradient vanishing, and improves generalization to time-variant wireless channels.
- Hierarchical learning-based approach integrates model-based optimization with deep reinforcement learning for efficient IRS phase shift adaptation and power allocation.
- Extreme Value Theory (EVT) is used for asymptotic performance analysis, optimizing beamforming strategies under extreme network conditions for robustness.
- Multi-agent collaboration between IRS, base station, and users reduces signaling overhead and computational complexity while improving network adaptability.
- The approach enhances scalability, reliability, and computational efficiency, ensuring faster convergence and improved spectral and energy efficiency.

### **Work Flow**



# **Block Diagram**



#### TECHNOLOGY USED

#### Deep Reinforcement Learning (DRL)

- Deep Q-Network (DQN)
- Deep Deterministic Policy Gradient (DDPG) Actor-Critic Architecture
- Replay Buffers
- Reward-Based Optimization

#### **Machine Learning Libraries**

- PyTorch for model training and inference.
- SciPy

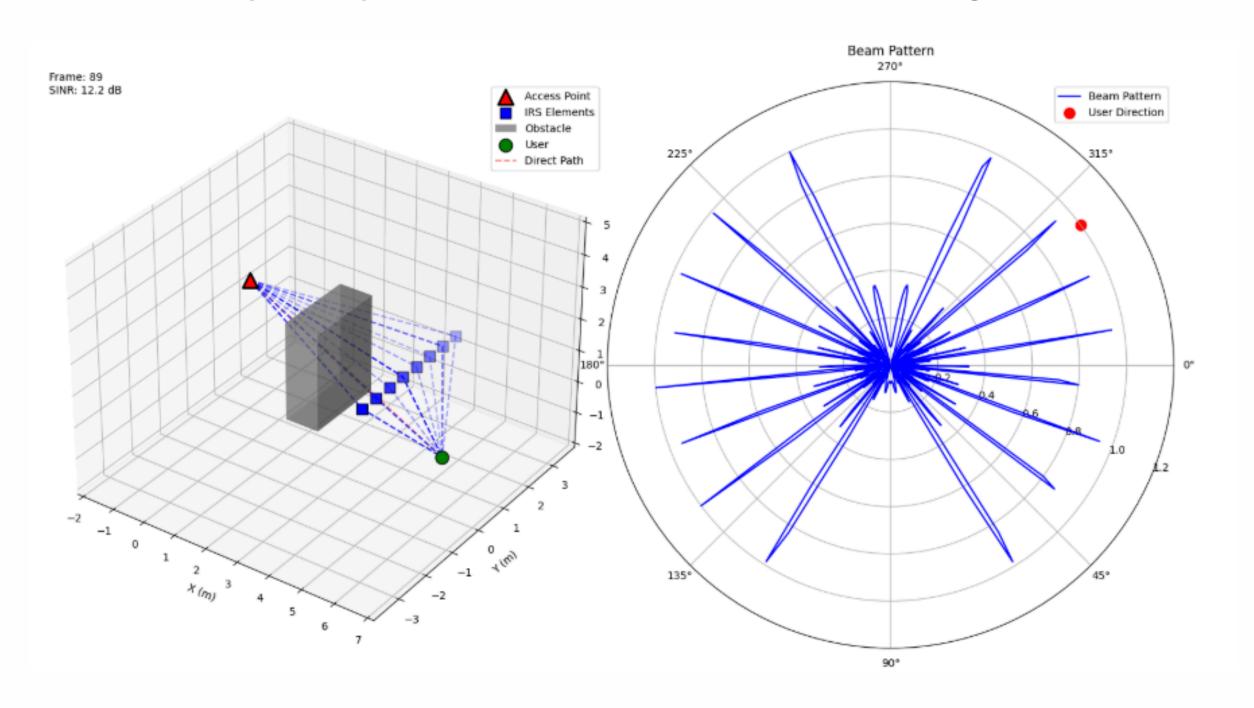
#### **Visualization Tools**

 MATPLOTLIB -Used for plotting results like SINR vs BER, phase shift variations, 3D signal strength patterns, etc.

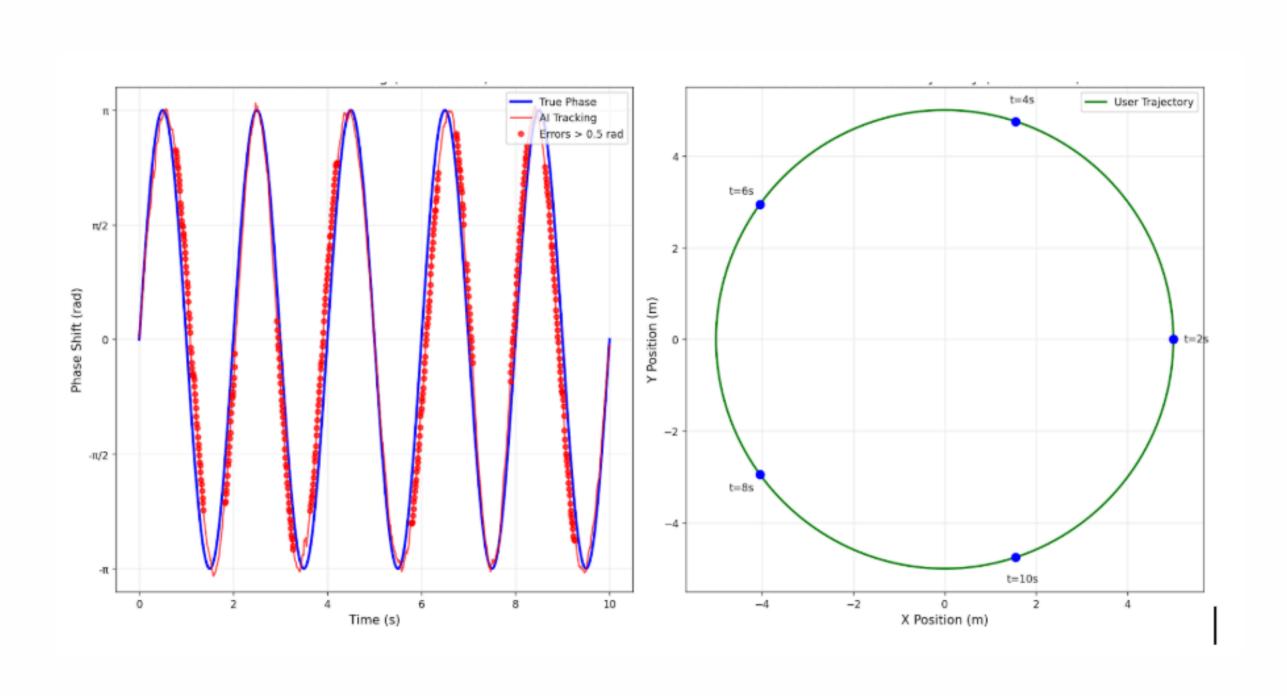
#### **Simulation Parameters**

| Parameters             | Values                         |  |
|------------------------|--------------------------------|--|
| Carrier Frequnecy      | 2.4GHz                         |  |
| Transmit Power (BS)    | 30dBm                          |  |
| Noise Floor            | -90 dBm                        |  |
| IRS Configuration      | 8-element uniform planar array |  |
| Base Station Position  | (0, 0, 10 m)                   |  |
| IRS Panel Position     | (50 m, 0, 15 m)                |  |
| User Mobility          | Circular Trajectory            |  |
| Number of IRS elements | 8                              |  |
| User Velocity          | 5 km/h                         |  |
| Obstacle Location      | (25 m, 25 m, 25 m)             |  |
| Obstacle Size          | (10m, 20m, 50m)                |  |
| Channel                | Rayleigh Fading Channel        |  |

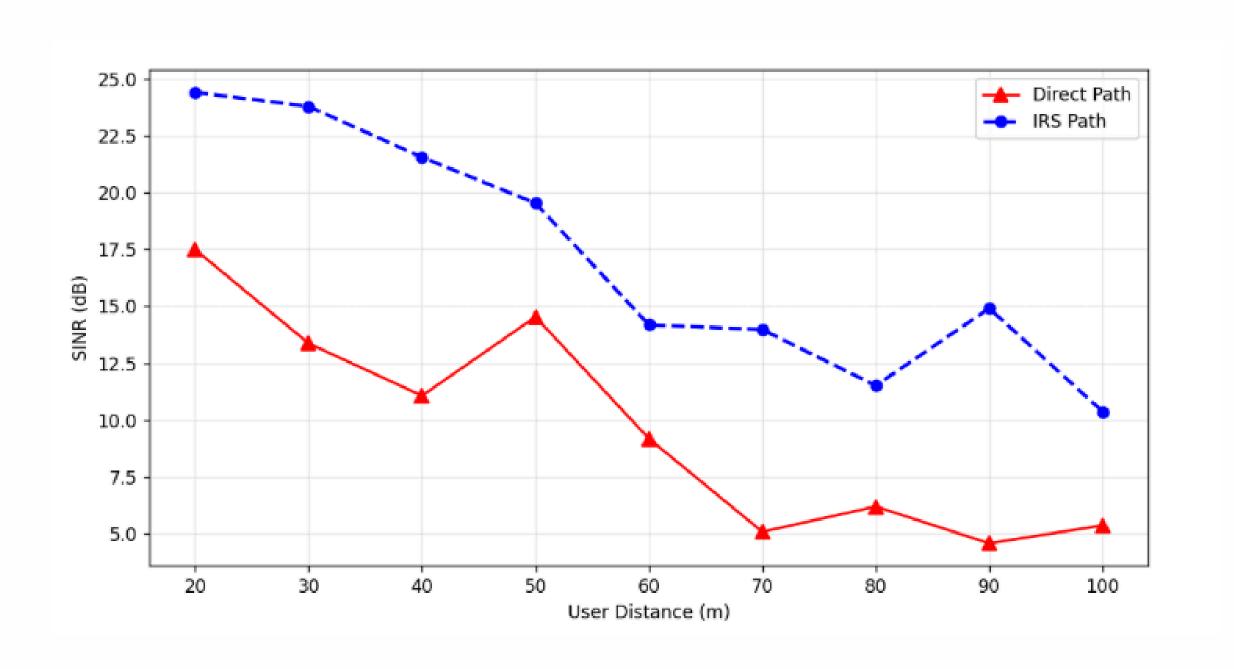
#### **User Trajectory Visualization and Beamforming Pattern**



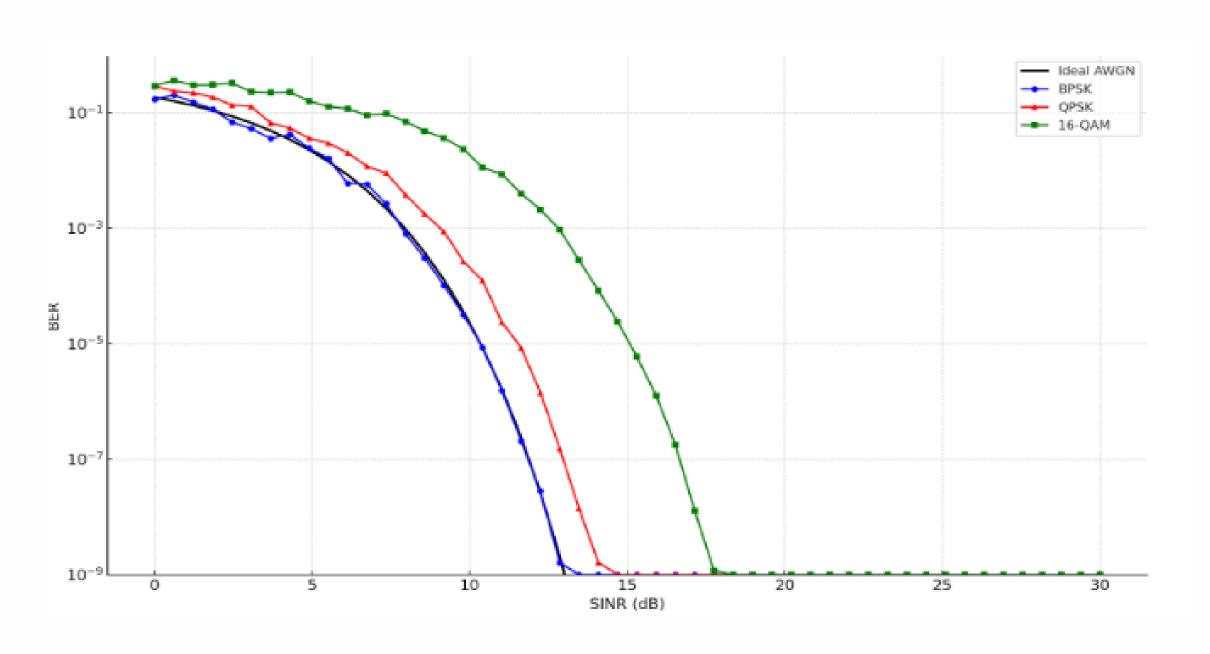
#### **Continuous Phase Shift**



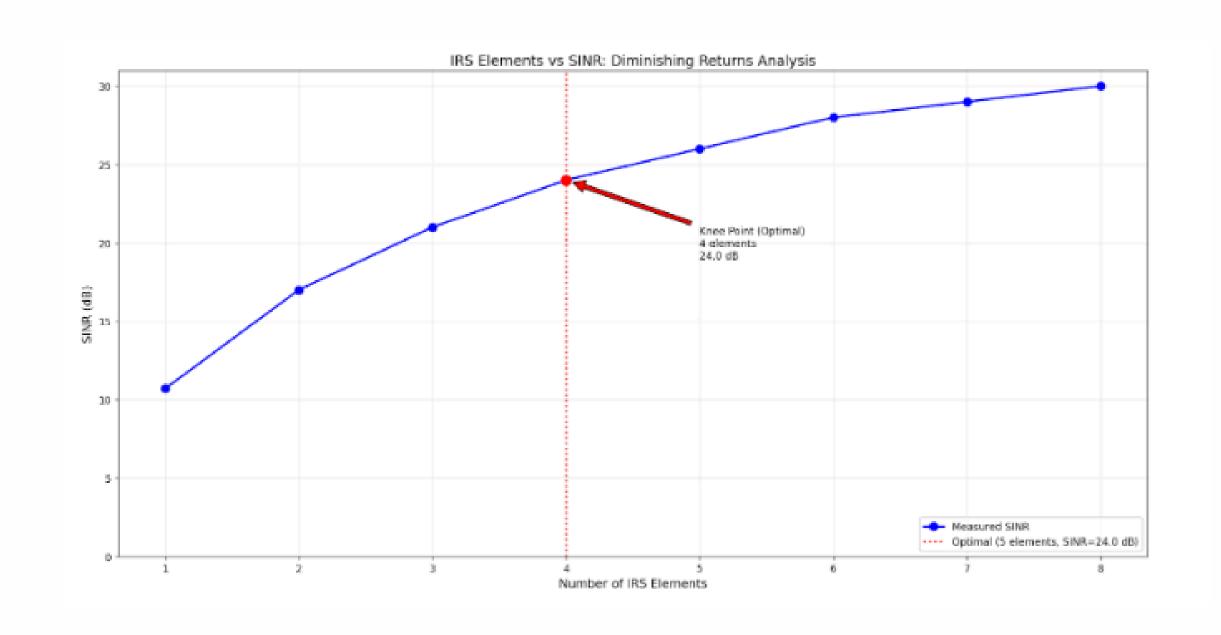
#### **User Distance vs SINR**



#### SINR vs BER



#### IRS elements vs SINR



### **Conclusion and Future Work**

- AI-driven IRS optimization significantly enhances 5G coverage, reduces energy consumption, and improves network efficiency.
- The system dynamically adjusts IRS phase shifts using Deep Reinforcement Learning (DRL) for real-time signal adaptation.
- Implementing the AI model on an IRS controller enables continuous learning and adaptation in changing environments.
- Future work includes expanding to 6G networks, integrating THz communication, and optimizing AI models for faster real-time processing.
- Research will focus on hardware efficiency improvements, reducing computational overhead, and enhancing multi-user beamforming capabilities.
- The system can be extended for smart cities, IoT, autonomous vehicles, and satellite-based communication to further enhance global connectivity.

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# Thank you