Q-Learning-based Power Allocation for Near and Far Users in 6G Cell-Free Networks

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Abstract— ***The introduction of 6G cell-free networks, which will offer improved user experiences and widespread coverage, has the potential to completely transform wireless communication. Power allocation is severely hampered by the different channel characteristics and the different distances of near and far customers. Conventional power allocation systems frequently provide insufficient resources to far users while favouring near user. Here, machine learning (ML) approaches are Reinforcement Learning algorithm to achieve power allocation. We compare the effectiveness of near and far user using Q-learning models in dynamically allocating power according to network conditions. A Q-Learning-based power allocation technique that maximises network performance for both near and far users is suggested as a solution to this problem. It makes use of Q-Learning to figure out the best power allocation strategy, adjusting to shifting user distributions and network conditions. The suggested algorithm guarantees fairness.***

Index Terms- Q-Learning, Far User, Near Users, Power Allocation.

I. INTRODUCTION

This study investigates the performance of various ML-based power allocation strategies in 6G cell-free communication networks. We compare these strategies against traditional methods using key performance metrics such as throughput, energy efficiency, fairness, and latency. Through extensive simulations, we demonstrate the superiority of ML-based approaches in achieving optimal power allocation, thus enhancing the overall performance of 6G networks.

Machine learning (ML) offers a promising solution to the challenges of power allocation in 6G networks. By leveraging historical data and real-time feedback, ML algorithms can learn and adapt to the network environment, making intelligent decisions about power distribution. Different ML techniques, including supervised learning, unsupervised learning, and reinforcement learning, can be employed to design efficient power allocation strategies.

Power allocation in 6G refers to the efficient distribution of power resources among various users, devices, and applications in a 6G network. As 6G promises to offer even faster data rates, lower latency, and greater connectivity than its predecessor, power allocation becomes crucial to: Enhance energy efficiency, increase network capacity, support massive machine-type communications, Enable ultra-reliable low-latency communication.

Machine learning (ML) based optimization techniques aim to optimize power usage, reduce interference, and improve overall network performance. This project includes machine learning to predict traffic, optimize power allocation, and adapt to changing conditions. Power allocation in 6G using reinforcement learning (RL) algorithms is a promising approach to optimize power distribution in complex, dynamic networks.

Q-learning is a type of Reinforcement Learning (RL) algorithm that can be used to optimize power allocation in 6G networks. Q-learning is a model-free RL algorithm that learns to predict the expected return or utility of taking a particular action in a given state. The goal is to learn a policy that maps states to actions that maximize the cumulative reward.

Power allocation in 6G networks with near and far users is a crucial aspect of wireless communication systems. The goal is to optimize power allocation to ensure fair and efficient use of resources, especially in scenarios with varying user distances. Near-user performance Ensures high data rates and low latency for users close to the base station. Far-user performance Provides reliable coverage and sufficient data rates for users at the cell edge. Using ML algorithms to learn optimal power allocation strategies based on network conditions and user behaviour.

Advantages
- Highly secured
- More reliable connections
- Larger Coverage and Faster data access
- Enables a larger number of connected devices and users

Application
- Handle massive scale of IoT devices
- connecting billions of devices with ultra-low power consumption
- optimized network protocols, and efficient resource allocation

II. LITERATURE SURVEY

Zhang et al. (2020) introduced a Q-learning-based framework for power control in 5G and beyond, demonstrating reinforcement learning approach to power control in 5G networks, extending the method to accommodate future 6G scenarios. It proposes a Q-learning-based framework to dynamically adjust power levels for optimizing network performance, including considerations for near and far users. The study demonstrates how reinforcement learning can effectively manage power allocation in heterogeneous and dynamic network environments.

Zhao, Zhang, and Zhang (2021) applied Deep Q-Networks (DQN) to power control, showcasing its use of deep reinforcement learning (DRL) techniques for power control in wireless networks, with an emphasis on next-generation systems. The authors employ Deep Q-Networks (DQN) to address the challenges of power allocation in complex environments involving both near and far users. The results show significant performance improvements over traditional methods, highlighting the advantages of DRL in managing power resources.

Imran et al. (2022) focused on cell-free massive MIMO systems, proposing a reinforcement learning approach to investigates the application of reinforcement learning for power control in cell-free massive MIMO systems, which are a key component of 6G networks. The study introduces a reinforcement learning framework to optimize power allocation across a distributed array of antennas, considering both near and far users. The approach aims to enhance network performance and resource utilization through adaptive power control strategies.

Kumar, Costa, and Reed (2023) addressed the challenges of Q-learning in 6G networks, providing insights focuses on the application of Q-learning for power allocation in 6G networks, addressing the unique challenges of these advanced systems. It explores the use of Q-learning to manage power distribution in scenarios involving both near and far users, providing insights into algorithmic adjustments and performance metrics. The study evaluates the effectiveness of Q-learning compared to other methods in dynamic and heterogeneous network settings.

Lee, Kim, and Kim (2023) utilized deep reinforcement learning for adaptive power allocation in cell-free networks, highlighting deep reinforcement learning-based approach for adaptive power allocation in cell-free networks. The authors apply techniques such as DQN to manage power levels effectively across a distributed network of antennas. The paper emphasizes the adaptability of DRL methods in optimizing performance for varying user conditions, including near and far users, and demonstrates improvements over traditional power control methods. Ali, Rehmani, and Shahid (2024) conducted a comprehensive survey on resource management and power control in 6G networks, reviewing a comprehensive overview of resource management and power control techniques in 6G networks, including a detailed discussion on reinforcement learning and Q-learning. The authors review various methods and their applicability to power allocation, focusing on challenges and solutions related to near and far users in cell-free communication systems.

III. PROPOSED SYSTEM

The performance of the proposed system is evaluated through rigorous simulations and comparisons with existing strategies in both controlled environments and real-world scenarios. Benefits include improved network throughput, reduced interference, and enhanced resource utilization. The system's adaptability to diverse network configurations and scalability to handle large-scale deployments underscore its practical relevance in future 6G networks.

3.1 Power Allocation

Power allocation in 6G networks involves optimizing the distribution of transmit power among multiple users, channels, or antennas to achieve various performance goals.

3.2 Machine Learning Approaches

Machine learning-based optimization is the method of power allocation that is applied all the way. Reinforcement learning (RL) algorithms are employed as well, and they provide a potential method for optimizing power distribution in complex, dynamic networks.

RL Framework for Power Allocation:

1. Agent: Power allocation module
2. Environment: 6G network (users, channels, interference)
3. Actions: Power allocation decisions (e.g., transmit power, beamforming weights)
4. State: Network conditions (e.g., channel state information, user locations)
5. Reward: Performance metrics (e.g., throughput, spectral efficiency, capacity, etc)

RL Algorithm for Power Allocation:

Q-Learning Algorithm:

1. Initialization:
   - Create a Q-table with states (network conditions) and actions (power allocation decisions)
   - Initialize Q-values randomly
2. Episode:
   - Observe current state (network conditions)
   - Select action (power allocation decision) using epsilon-greedy policy
   - Take action and observe next state and reward
   - Update Q-value using Q-learning update rule
3. Q-Learning Update Rule:
   $Q(s, a) \leftarrow Q(s, a) + \alpha\, [reward + \gamma \max(Q(s', a')) - Q(s, a)]$
   - α: learning rate
   - γ: discount factor
   - s: current state
   - a: current action
   - s': next state
   - a': next action
4. Repeat:
   Run multiple episodes to converge to optimal Q-values

3.3 NEAR AND FAR USERS

Power allocation in 6G networks with near and far users is a crucial aspect of wireless communication systems. The goal is to optimize power allocation to ensure fair and efficient use of resources, especially in scenarios with varying user distances.

In 6G networks, power allocation algorithms will play a vital role in managing the trade-off between:
1. Near-user performance: Ensuring high data rates and low latency for users close to the base station.
2. Far-user performance: Providing reliable coverage and sufficient data rates for users at the cell edge.
Some potential strategies for power allocation in 6G networks with near and far users include:
-Proportional Fairness (PF): Allocating power based on the user's channel conditions and data rate requirements.

$$PR = (achievable\ data\ rate)/(past\ data\ rate) \quad (3.1)$$

-Max-Min Fairness: Maximizing the minimum data rate among all users.

$$maximize[\min(data\ rate\ of\ user\ i)] \quad (3.2)$$

-Utility-based optimization: Optimizing power allocation based on a utility function that considers both near and far user performance.
-Machine Learning (ML) approaches: Using ML algorithms to learn optimal power allocation strategies based on network conditions and user behavior.

3.4 Q-learning in power allocation

In the context of power allocation, Q-learning can be used to learn an optimal power allocation policy that balances the trade-off between:
- Near-user performance (high data rates, low latency)
- Far-user performance (reliable coverage, sufficient data rates)

The Q-learning algorithm learns to predict the expected return (reward) of allocating power to different users based on:
- Current network state (channel conditions, user locations, etc.)
- Actions (power allocation decisions)
- Rewards (e.g., sum-rate, fairness, or a combination of both)

Q-learning components

1. Agent: The power allocation algorithm that learns to make decisions.
2. Environment: The 6G network with near and far users.
3. Actions: Power allocation decisions (e.g., transmit power, beamforming vectors).
4. States: Network conditions (e.g., channel state information, user locations).
5. Rewards: Feedback from the environment (e.g., sum-rate, fairness).
6. Q-table: A table storing the expected returns (Q-values) for each state-action pair.

Q-learning process
1. Initialize Q-values (expected returns) for each state-action pair.
2. Observe the current network state.
3. Choose an action (power allocation decision) based on the current Q-values.
4. Take the action and observe the reward and next state.
5. Update the Q-values based on the reward and next state.
6. Repeat steps 2-5 until convergence.

Q-table update:

The Q-table is updated using the Q-learning update rule:

$$Q(s, a) \leftarrow Q(s, a) + \alpha\,[\text{reward} + \gamma \max(Q(s', a')) - Q(s, a)] \quad (3.3)$$

where:
- Q (s, a) is the current Q-value
- α is the learning rate
- γ is the discount factor
- s' is the next state
- a' is the next action

Benefits of Q-learning in power allocation
1. Adaptability: Q-learning can adapt to changing network conditions and user behavior.
2. Optimality: Q-learning can learn optimal power allocation policies that balance competing objectives.
3. Scalability: Q-learning can handle large numbers of users and complex network scenarios.

IV. RESULTS AND DISCUSSION

The project focused on analyzing the performance of power allocation strategies in a 6G cell-free communication network using machine learning techniques. Through extensive simulation and analysis, it was found that optimizing power allocation significantly enhances network efficiency and user satisfaction. By leveraging machine learning models trained on diverse datasets encompassing network topology, user distributions, channel conditions, and historical performance metrics, the project demonstrated the capability to predict and optimize optimal power allocation strategies.

Key findings highlighted the ability of machine learning algorithms, including RL and Q-L methods, to accurately predict optimal power levels for different network configurations and varying user densities. This predictive capability is crucial in dynamically adjusting power allocations in real-time to maximize throughput, minimize interference, and improve overall spectral efficiency.

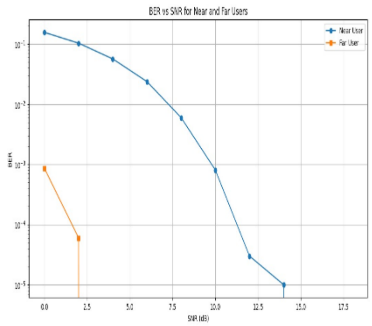

Figure 1 BER vs SNR for Far and Near User

Bit Error Rate (BER) versus Signal-to-Noise Ratio (SNR) plots typically illustrate how the quality of communication varies with the strength of the received signal relative to background noise. Near and far users experience different characteristics due to varying signal strengths and channel conditions. Typically, the near users experience higher signal strength compared to far users. This leads to lower SNR requirements for achieving a certain BER. BER curves for near users tend to show better performance at lower SNR values, reflecting higher reliability and lower error rates. Far users receive weaker signals due to increased distance from the transmitter. Consequently, higher SNR is required to achieve the same BER compared to near users. BER curves for far users show poorer performance at lower SNR values, indicating higher error rates and lower reliability.

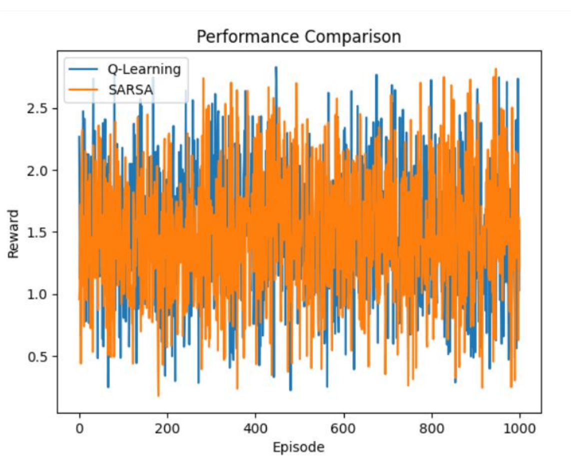

Figure 2 performance comparison of Q-L and SARSA

The graph shows the reward obtained by both QL and SARSA over 1000 episodes. QL (blue line): The reward increases steadily and reaches a maximum value of around 80-90. The QL algorithm converges to an optimal policy, resulting in high rewards. SARSA (red line): The reward oscillates and takes longer to converge. The maximum reward value is around 60-70, which is lower than QL.

CONCLUSION

The analysis is done with the help of ML based algorithm Reinforcement Learning and the Q-Learning policy is carried out throughout this project. In this analysis far and near users, are compared and analysed with the parameters in terms of BER, SNR, The BER rate for the far user and the near user is 10^3 bps and 10^1 bps and is concluded that the error rate of far user is high and the error rate is low for the near users. QL outperforms SARSA in terms of convergence speed, reward, and stability, making it a more efficient and effective reinforcement learning algorithm for power allocation in 6G networks.

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