Intelligent Multi-Link Selection for IEEE 802.11be Using Reinforcement Learning with Radiation Pattern Awareness

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***Abstract*— The IEEE 802.11be (Wi-Fi 7) standard introduces Multi-Link Operation (MLO) to enhance network efficiency by enabling simultaneous data transmission across multiple frequency bands. However, optimal link selection in dynamic wireless environments remains a significant challenge due to fluctuating signal conditions, interference, and the impact of antenna radiation patterns. Traditional heuristic-based approaches often fail to adapt effectively to these variations, leading to suboptimal performance. This paper proposes an intelligent Multi-Link selection framework based on Reinforcement Learning (RL), incorporating radiation pattern awareness to enhance decision-making. The proposed model leverages both omnidirectional and directional beamforming characteristics to dynamically select the most efficient link, considering real-time network conditions such as signal strength, interference, and spatial coverage. By integrating radiation pattern information into the RL training process, the system optimizes link selection while minimizing latency and improving throughput. Simulation results demonstrate that the proposed RL-based approach can select links based on various factors and dynamically choose the optimal link in real-time. This study highlights the potential of RL-driven Multi-Link selection strategies in advancing next-generation Wi-Fi networks and adaptive wireless communication systems.**

Keywords*— *Multi-Link Operation, reinforcement learning, wireless networks

I. Introduction

Wireless communication is a cornerstone of modern networks, supporting applications such as high-definition video streaming, industrial automation, and the Healthcare Internet of Things (H-IoT) [1]. As user demands increase, networks must provide higher data rates, lower latency, and reliable connectivity. To meet these challenges, the IEEE 802.11be standard, commonly known as Wi-Fi 7, introduces Multi-Link Operation (MLO), a key innovation that enables devices to simultaneously utilize multiple frequency bands to enhance throughput and minimize latency. MLO allows a wireless station (STA) to establish concurrent connections with an access point (AP) across 2.4 GHz, 5 GHz, and 6 GHz bands, supporting parallel data transmission over multiple channels and improving network congestion and transmission reliability. The MLO process requires simultaneous data acquisition and transmission (STR), which introduces a link selection challenge [2]. Furthermore, addressing parallel backoffs can mitigate the latency issue [3]–[6]. The radiation pattern significantly affects network performance when data is transmitted simultaneously. Specifically, it impacts the hidden node problem [7] and interference [8], [9], which in turn degrade communication efficiency. This degradation results in increased delay and reduced throughput, making it essential to consider the impact of radiation patterns on link selection. To address this challenge, Reinforcement Learning (RL) has emerged as a powerful approach for optimizing dynamic link selection. RL enables adaptive decision-making by assigning rewards and penalties based on network conditions. Recent research has demonstrated the effectiveness of RL in wireless communication by enhancing network efficiency and reducing interference [10], [11]. Additionally, antenna radiation characteristics have been considered in multi-link transmission, as demonstrated by [12], which developed a 2×2 MIMO antenna to support multi-link applications. Furthermore, [13] proposed a PHY and MAC layer analysis model to improve overall Wi-Fi 7 performance.

This paper proposes an RL-based Multi-Link selection framework that incorporates radiation pattern awareness to improve Wi-Fi 7 network performance. Unlike traditional heuristic approaches, the proposed RL model dynamically selects the most suitable multi-link configuration by analyzing RSSI, Signal-to-Noise Ratio (SNR), interference levels, throughput variations, and antenna radiation characteristics. The proposed RL-based model continuously learns and adapts to varying network conditions, ensuring optimal link selection and improved network efficiency.

This paper is organized into five sections. Section II presents the channel model used for Multi-Link Operation, including path loss modeling, small-scale fading effects, interference modeling, and the impact of radiation patterns on link performance. Section III describes the RL framework, state-action-reward formulation, and the selected RL algorithms. Section IV details the simulation setup and performance evaluation, comparing the proposed RL-based Multi-Link. Section V concludes the paper by summarizing key findings and suggesting future research directions.

II. CHANNEL MODEL

The performance of wireless communication systems is largely influenced by the characteristics of the wireless channel like radiation pattern in Fig.1. In the context of MLO in IEEE 802.11be (Wi-Fi 7), the effectiveness of simultaneous data transmission across multiple frequency bands depends on several factors, including path loss, fading, interference, and antenna radiation patterns. This section presents the channel model used to evaluate the MLO system, with particular attention given to the impact of each factor on link performance.

A. Path Loss Model

Path loss refers to the reduction in signal strength as the transmitted signal travels through space. In wireless communication systems, path loss is influenced by the distance between the AP and STA, as well as the environment (e.g., urban, indoor, or rural settings). To model path loss, the log-distance path loss model is commonly used, given by the following equation:

$$P_L(d) = P_{L0} + 10n\log\frac{d}{d_0} \tag{1}$$

where $P_L(d)$ is the path loss at distance d,
P_{L0} is the reference path loss at d_0,
n is the path loss exponent,
d is the distance between the AP and STA,
d_0 is the reference distance.

For the Wi-Fi 7 network operating in the 2.4 GHz, 5 GHz, and 6 GHz bands, the path loss exponent is assumed to be different for each frequency band due to varying signal attenuation characteristics. Higher frequencies, such as 6 GHz, typically suffer from greater path loss compared to 2.4 GHz and 5 GHz.

B. Fading Model

Fading is caused by the interference of multiple signal paths, leading to variations in signal strength over time or space. Small-scale fading is particularly important in wireless communication, as it can cause rapid fluctuations in signal quality due to factors like multipath propagation and shadowing. The Rayleigh fading model is often used to model fading in environments with no line-of-sight (NLOS), while the Rician fading model is applied in line-of-sight (LOS) scenarios. In our model, Rayleigh fading is assumed to represent the fading effect for the wireless links between AP and STA, as the environment is typically non-line-of-sight in many urban or indoor scenarios.

C. Interference Model

Interference arises from multiple transmitters operating on Interference plays a critical role in determining the quality of wireless communication systems, especially in MLO environments where multiple links operate concurrently across different frequency bands. In these systems, interference typically arises from external sources or other transmissions within the same environment, which can cause signal degradation and loss of data. In our model, interference is calculated based on the radiation pattern and signal strength of the transmission. For omnidirectional transmission, interference is randomly generated between 0 and 10 dB, simulating external sources of interference. For directional

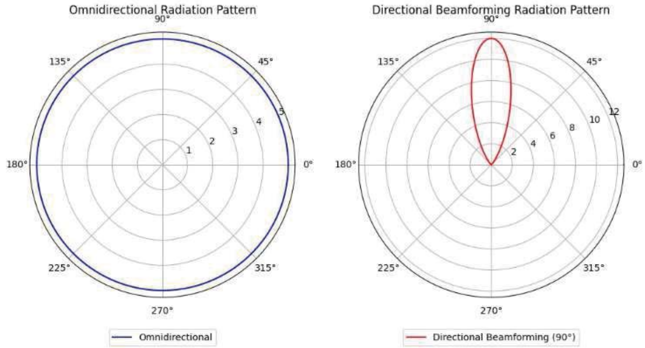

Fig.1. The radiation pattern for Multi-Link Operation (MLO).

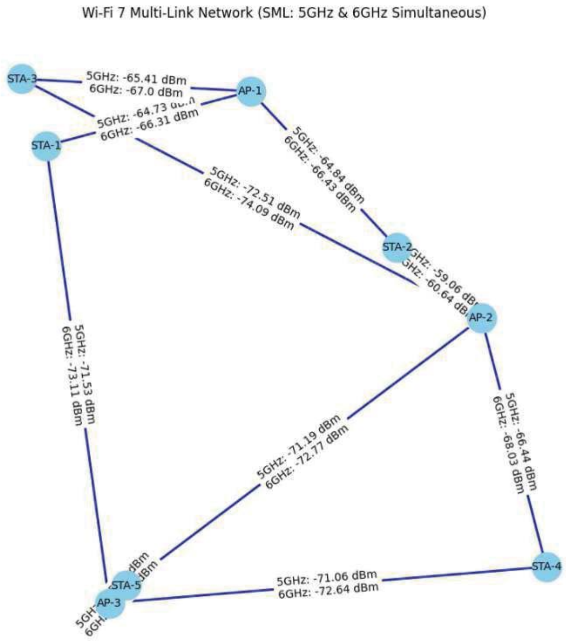

Fig. 2. The MLO with AP and STA environment.

beamforming, interference is calculated using the gain of the antenna, which is influenced by the beam width and beam angle. The interference value increases with the antenna's gain, as higher gain often leads to more focused transmission, thus increasing the potential for interference in adjacent regions. The impact of interference on the signal quality is evaluated through the signal-to-interference-plus-noise ratio (SINR). SINR is a crucial parameter in wireless communication, as it determines the quality of the received signal relative to interference and noise. In this model, interference is treated as a factor that reduces SINR, thereby negatively affecting throughput and latency. Mathematically, the SINR for each link is computed as:

$$SINR = \frac{RSSI}{Interference + Noise} \tag{2}$$

where $RSSI$ is the received signal strength,
$Interference$ is the interference caused by other transmissions in the environment (dB),
$Noise$ is the background noise level (dBm).

The Interference for each frequency band (5 GHz and 6 GHz) is considered independently. Interference values are generated dynamically based on the radiation patterns and signal conditions of the system, simulating real-world environments where interference levels vary depending on factors like user mobility, distance from AP, and obstructions. The interference model is thus essential for simulating realistic wireless environments and for optimizing the performance of the proposed RL framework.

D. Throughput

Throughput is a key performance metric that measures the actual rate of successful data transmission in a wireless communication system. In the context of MLO and the IEEE 802.11be (Wi-Fi 7) standard, throughput is particularly important because it determines the system's ability to handle high data rates and multiple simultaneous transmissions across different frequency bands. In this model, throughput is calculated for both the 5 GHz and 6 GHz bands, as well as for the overall system when using MLO, which combines the throughput from both frequency bands to provide enhanced data rates. The total throughput is the sum of the individual throughputs from each link, considering the simultaneous use of multiple links. The throughput for each link is estimated using the Shannon Capacity Formula, which defines the theoretical upper bound of the data transmission rate in a communication channel with a given Signal-to-Noise Ratio (SNR). The formula is expressed as:

$$C = B\log_2\left(1+SNR\right) \tag{3}$$

where C is the channel capacity or throughput,

B is the bandwidth of the channel,

SNR is the signal-to-noise ratio (in linear scale).

For Wi-Fi 7, the system operates on a bandwidth of 160 MHz for each frequency band (5 GHz and 6 GHz). The throughput for each frequency band is calculated as:

$$T = B\log_2\left(1+10^{\frac{SNR}{10}}\right) \tag{4}$$

The SNR is obtained from the previous step, and B represents the bandwidth, which is 160 MHz for 5 GHz and 6 GHz channels. The total throughput for MLO is calculated by summing the individual throughputs from the 5 GHz and 6 GHz links:

$$T_{MLO} = T_{5GHz} + T_{6GHz} \tag{5}$$

This combined throughput allows for higher data rates and better utilization of available spectrum, enabling the system to handle more data while reducing latency compared to single-link operation following Fig.2. In addition to the basic throughput calculation, throughput efficiency is also affected by factors such as interference, latency, and signal degradation. The presence of interference, as modeled in the previous section, can lower the effective throughput by reducing the SINR, which directly impacts the data rate that can be achieved on each link. To evaluate the system's efficiency, we also calculate the percentage increase in throughput when using MLO as compared to using a single frequency band (5 GHz or 6 GHz). This allows us to assess the benefits of multi-link operation in improving the overall network performance.

III. Reinforcement Learning Model

The Reinforcement Learning (RL) model is designed to optimize the link selection process in MLO for Wi-Fi 7 (IEEE 802.11be). The goal is for the RL agent to dynamically select the best link configuration, whether using 5 GHz, 6 GHz, or MLO, based on real-time network conditions such as RSSI, SNR, latency, throughput, and interference.

A. Reinforcement Learning Framework

The RL framework follows a Markov Decision Process (MDP), where the state, action, and reward are defined to guide the agent in selecting the optimal link configuration. The system’s state S includes real-time network parameters, and the agent’s goal is to choose an action A that maximizes the long-term reward R.

- State (S): Includes network conditions such as RSSI, SNR, latency, throughput, and interference for both 5 GHz and 6 GHz links.
- Action (A): The RL agent chooses between three actions: 5 GHz, 6 GHz, or MLO (multi-link operation using both 5 GHz and 6 GHz bands).
- Reward (R): The reward is computed based on the throughput, latency, and interference of the selected action. The reward function aims to maximize throughput while minimizing latency and interference.

B. RL Algorithm Selection

The RL-based AP-STA Link Selection uses a straightforward approach where the agent observes the network state (e.g., RSSI, SNR, throughput, interference) and selects the best link between 6 GHz or MLO. The RL model evaluates the current state and chooses an action based on predefined thresholds, optimizing the selection process. The model is trained iteratively with a reward function based on throughput and latency, allowing it to adapt to dynamic network conditions until convergence is reached.

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Pseudocode for RL-based AP-STA Link Selection
1. Initialize:
   - Set up AP and STA positions in a 2D space.
   - Define network parameters (RSSI, SNR, Throughput).
   - Define action space {6GHz, MLO}.
2. For each STA:
   - Observe state: (RSSI, SNR, Throughput, Interference).
   - Use RL model to select action:
   - If SNR and Throughput for 6GHz > Threshold →
     Choose 6GHz.
   - Otherwise, choose MLO.
3. Update RL Model:
   - Apply reward function based on throughput and
     latency.
   - Train model iteratively.
4. Repeat until convergence.
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IV. Result and Discussion

The results of this study present an in-depth analysis of the throughput performance in Wi-Fi 7 (IEEE 802.11be) Multi-Link Operation (MLO), incorporating reinforcement

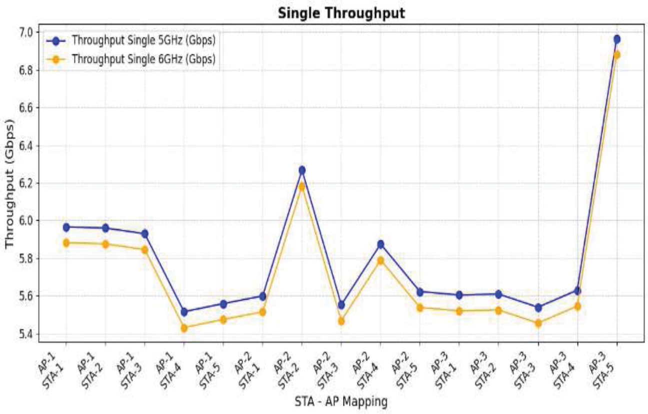

Fig.3. Single throughput for 5 GHz and 6 GHz.

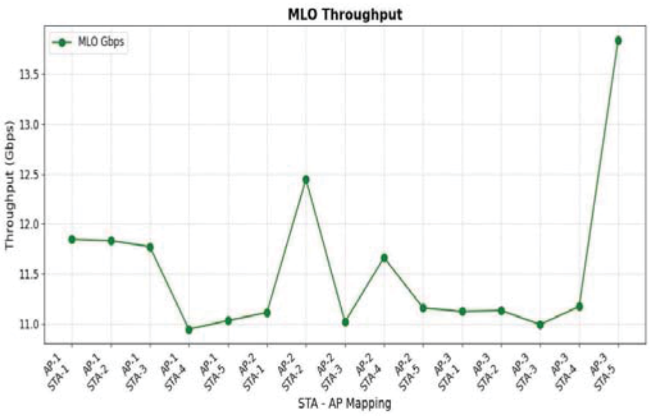

Fig.4. MLO throughput performance.

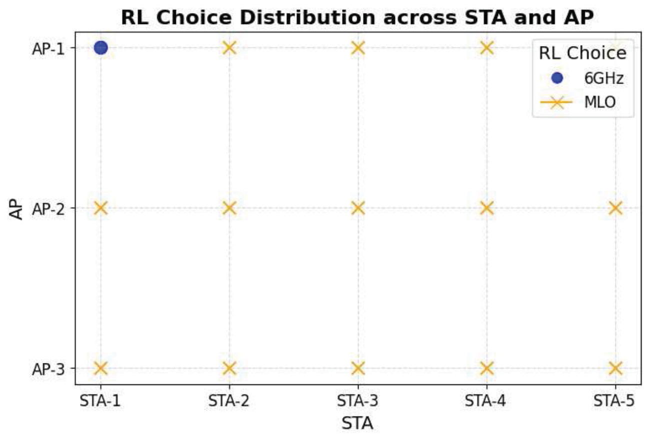

Fig.5. RL choice distribution across STA and AP.

learning (RL) for dynamic link selection, considering the impact of antenna radiation patterns. Figure 3 compares the single throughput performance between the 5 GHz and 6 GHz bands. The throughput of the 6 GHz band outperforms the 5 GHz band in all AP-STA pairs, primarily due to its higher bandwidth capacity. However, in the presence of obstacles, the 5 GHz band showed better performance compared to the 6 GHz band, as it is less susceptible to signal degradation. Figure 4 highlights the throughput performance when both 5 GHz and 6 GHz bands are used in MLO mode. The throughput increase is significant, with an improvement of up to 98.79% for the 5 GHz band and 101.55% for the 6 GHz band, demonstrating the advantages of combining both frequency bands. The RL-based link selection, as shown in Figure 5, dynamically adapts to varying network conditions. The algorithm selects the 6 GHz band for AP1 and STA1, while other AP-STA pairs utilize MLO. The RL agent's decision-making process considers key factors such as path loss, distance, and interference. For example, when interference is high or when signal strength is suboptimal for a single frequency band, the RL model opts for MLO to mitigate performance degradation and optimize throughput.

V. Conclusion

In this paper, we proposed an intelligent Multi-Link Operation (MLO) framework for Wi-Fi 7 (IEEE 802.11be) using Reinforcement Learning (RL) with radiation pattern awareness for optimized link selection. The results show that MLO significantly improves throughput by up to 101.55% compared to single-band operation. This enhancement is due to the combined use of both 5 GHz and 6 GHz bands, improving spectrum utilization and reducing latency. The RL-based model adapts to dynamic network conditions, selecting the optimal link configuration in real time, thus enhancing overall network efficiency.

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