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Wi-Fi 7 Optimization In High Density Environment

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Abstract:
Wi-Fi 7 (IEEE 802.11be) is the latest technology in wireless networking which helps to improve the performance of the network in dense wireless networks. In this work, an intelligent Wi-Fi 7 framework is proposed using reinforcement learning (RL) by implementing Q-learning algorithm. Baseline scheme makes use of Multi-link Operation (MLO) in 2.4GHz and 5GHz frequency bands while the suggested scheme employs Multi-Link Operation (MLO) in 2.4GHz, 5GHz, and 6GHz frequency bands along with TWT and Channel Puncturing. Both the frameworks are tested on the basis of throughput, latency, energy efficiency, and interference reduction. The experimental results show that the RL-based Wi-Fi 7 framework gives better throughput by 25%-28%, better energy efficiency by 25%-30%, reduced latency by 45%-50%, and 3× greater interference reduction than the baseline Wi-Fi 7 framework.

Key Word: *Multi link operation (MLO), Target Wake Time (TWT), Channel Puncturing, Q- Learning, Reinforcement Learning, Wi-Fi 7*

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I. Introduction

There is an increasing demand for wireless local area networks owing to the rapid proliferation of bandwidth and delay-sensitive applications such as video streaming, VR, AR, cloud gaming, and IoT services. [12] Although Wi-Fi 6 and Wi-Fi 6E have contributed towards improving spectral efficiency and network capacity, they do not possess the necessary abilities that can satisfy the requirements of next-generation applications in a dense and dynamic wireless environment. 6], [15], [23], [29]

Wi-Fi 7 intends to deliver multi-gigabit rates, ultra-low latency, and reliability through a variety of capabilities including 320 MHz channel bandwidth, 4096-QAM Modulation. [10], [15] Out of all the capabilities, MLO can be said to be one of the key innovations since it allows communication on multiple frequencies simultaneously, [1], [8], [22] thereby increasing throughput and transmission time. Other capabilities include TWT [11] and Channel puncturing. [5], [15], [17], [27]

It is evident from recent developments in AI and RL that there is significant scope in the area of wireless communications wherein the networks will be able to learn from the environment and make decisions on their own. There are several reinforcement learning techniques, among which Q-learning stands out as it is model free, computationally feasible, and learns the optimal policy through the interaction with the environment. [2], [9], [25], [29]

Purpose of research is to prove the possibility of adaptive reinforcement learning optimization that would help to improve the work of Wi-Fi 7 networks in a dense and dynamically changing environment of wireless networks.

Contributions of research:

The development of dynamic Wi-Fi 7 model using MLO over the 2.4 GHz, 5 GHz, and 6 GHz frequencies and TWT and Channel Puncturing technologies. A Q-learning algorithm is applied to make the Wi-Fi 7 network adapt intelligently to changing network conditions. The performance of both models is compared using throughput, latency, energy efficiency, and interference reduction. Improvement in the performance of the developed dynamic Wi-Fi 7 model due to increased throughput and energy efficiency and reduced latency and interference.

II. Literature Review

Evolution of Wi-Fi Technologies

Wi-Fi technologies have undergone a remarkable development since the advent of Wi-Fi 4 up to Wi-Fi 7 in order scope with the emerging requirements of high-speed wireless communications. [7], [12 [15] Whereas

IEEE 802.11n had MIMO capability and speeds of 600 Mbps, IEEE 802.11ac offered MU-MIMO and increased channel width. The IEEE 802.11ax, or Wi-Fi 6/6E, has raised the spectral efficiency and network capacity due to OFDMA and TWT. [4], [11], [23], In addition, the MLO feature, the use of 320 MHz channels, and MLO are available in Wi-Fi 7 (IEEE 802.11be) technology, [1], [30], making possible data rates up to 46 Gbps and providing future application such as augmented reality, virtual reality, and cloud gaming. [14]

Challenges in Wi-Fi 7 Networks

Wi-Fi 7 Q-learning based framework is likely to have issues such as training time being longer, higher computational costs, and the necessity for learning continuously in the changing network environment. The framework is dependent on network state information that is accurate and is prone to slow convergence with an increasing number of users and access points. Another challenge in using Q-learning with Wi-Fi 7 will be in the incorporation of MLO, TWT, and Channel Puncturing.

Applications of Reinforcement Learning in Wireless Networks

Reinforcement Learning (RL) approaches have been used in wireless network optimization due to their ability to learn through interactions with the environment and make decisions autonomously. The RL techniques continuously sense the state of the network, choose the proper action and get feedback from the environment in terms of reward. [9], [25], [32] This makes RL very appropriate in dealing with optimization problems in dynamic wireless networks. Past works have been able to apply reinforcement learning techniques in channel assignment, user association, traffic control and interference reduction problems. [13], [29], [31], [33]

Resource Optimization Based on Q-Learning

Q-Learning is among the most popular model-free Reinforcement Learning approaches that are widely used for network optimization. In this manner, it become possible to know the best action to be taken for a certain network scenario without any information about the environment. [16], [18], [21] Some scientific studies proved the applicability of the Q-Learning algorithm for enhancing such features of wireless networks as channel selection, spectrum usage, and resource allocation. With Q-Learning, state-action values keep being updated depending on rewards received and gradually reach optimal policy. However, there are many studies concerning the application of the Q-Learning technique to the past Wi-Fi generations or some specific optimization cases. [24], [28]

Table 1: Comparative Analysis of Existing Studies and Proposed Work

Author / year	Technique	Contribution	Research Gap
López-Pérez et al. 2019 [19]	IEEE 802.11be (Wi-Fi 7) architecture and key feature	Explained the structure and key features of Wi-Fi 7 architecture.	Absence of intelligent resource optimization.
Deng et al. 2020 [10]	MLO Performance Analysis	Analyzed the performance of Multi-Link Operation	Uses Static link management.
Khorov et al. (2020) [15]	IEEE 802.11be (Wi-Fi 7) Channel Puncturing	Described the channel puncturing process and key features of Wi-Fi 7 architecture	Absence of application of machine learning to optimize channel puncturing process based on changing network environment
Szott et al. 2022 [29]	Target Wake Time (TWT)	Enhancing energy efficiency by means of TWT	Using Fixed wake-up schedule.
Iturria Rivera et al. 2023 [13]	Deep RL for MLO	Optimization of traffic across multiple links Optimized traffic over multiple links.	Does not consider TWT and channel puncturing.
Liu et al. (2023) [20]	Reinforcement Learning	Application of RL technique for wireless optimization.	Absence of joint optimization of throughput, delay, interference, and Energy efficiency
Abdalhafid et al. (2024) [1]	MLO (2.4 and 5GHz)	Throughput and latency of Wi-Fi 7 analysis	Absence of energy efficiency with reinforcement learning
Author / year	**Technique**	**Contribution**	**Research Gap**
Almamoon Alauthman & Tamer Shraa (2025) [4]	Static Wi-Fi 7 Performance Evaluation using NS-3	Performance evaluation of Wi-Fi 7 in dense networks using MLO and compares with Wi-Fi 6 based on throughput, latency, jitter, and packet loss	Uses static optimization; no Q-learning-based dynamic resource allocation.
Proposed Work	Q-Learning + MLO + TWT + Dynamic Channel Puncturing	Best link selection, wake-up scheduling, and dynamic channel puncturing for improving throughput, latency, reducing interference and energy consumption.	Addresses dynamic resource optimization using Q-learning.

III. System Model & Mathematical Formulation

Network Model

Within the scope of the present research, an intensive wireless Wi-Fi 7 (IEEE 802.11be) network consisting of four Access Points (APs) with different numbers of users ranging from 50 to 100 has been used. The length of time of each simulation has been determined at 300 ms and repeated five times for obtaining averaged results. In the baseline Wi-Fi 7 network, Multi-Link Operation (MLO) is performed at 2.4 GHz and 5 GHz frequency bands with 320 MHz channel width. However, the dynamic Wi-Fi 7 solution is an upgrade of the basic architecture of Wi-Fi 7 by using MLO at 2.4 GHz, 5 GHz, and 6 GHz frequency bands as well as TWT and Channel Puncturing technologies.

The dynamic Wi-Fi 7 network operates by means of using a reinforcement learning technique. The Q-learning agent always observes the state of the network and makes decisions according to it. They include the decision on a certain strategy of transmission, the distribution of traffic among links, the scheduling of wake-up intervals through the TWT technology and avoidance of interfered parts of spectrum by means of Channel Puncturing technology. Primary purpose of the agent is to achieve maximum throughput with minimum energy consumption and interference. The overall network architecture is illustrated as a multi-access-point Wi-Fi 7 environment with adaptive resource management capabilities.

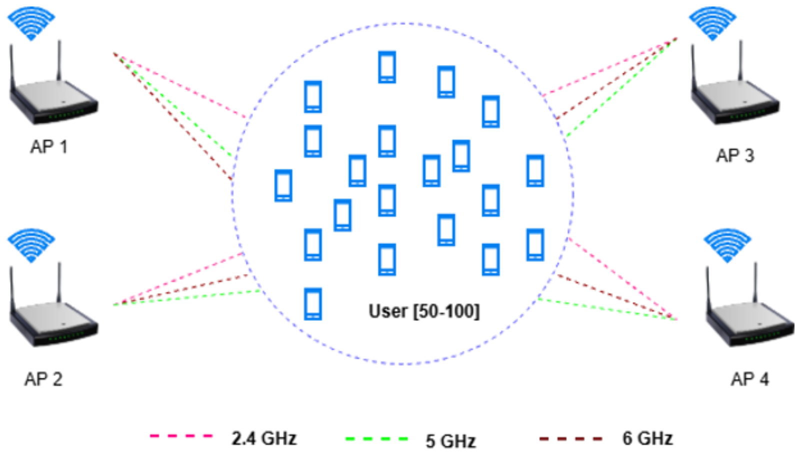

Figure 1: Network model

Mathematical Model

The mathematical model characterizes the wireless communication environment with basic equations such as received signal power and Signal to Interference plus Noise Ratio (SINR). These equations help in evaluating the link quality as well as form the foundation of the Q-learning optimization framework that has been proposed for Wi-Fi 7 networks.

Received Signal Power: The Received Signal Power can be defined as the amount of power received from the transmitter access point to the receiver user device in consideration of propagation losses. It is denoted by decibel milliwatts (dBm) [26].

$$P_r = P_t - PL(d) \tag{1}$$

Here P_r shows the power of the received signal in dBm, P_t is the power of signal that is transmitted in dBm. $PL(d)$ is the path loss in dB at a distance d.

Signal-to-Interference-plus-Noise Ratio (SINR): Signal to Interference plus Noise Ratio (SINR) measures the quality of the received wireless signals with respect to the comparison of received signal power and combined interference and noise power. A high value of SINR means better performance of the network. [26]

$$SINR_i = \frac{P_{r,i}}{I_i + N_0} \tag{2}$$

$P_{r,i}$ denotes the **received power** of the ith user I_i indicates **the interference power, and** N_0 is **the noise power,** with all measurements expressed **in dBm.**

Table 2: Channel Model Parameters

Parameter	Symbol	Value
Frequency Bands	f	2.4 GHz, 5 GHz (baseline); 2.4 GHz, 5 GHz, 6 GHz (Dynamic)
Channel Bandwidth	B	320 MHz
Number of Access Points	N_{AP}	4

Number of Users	N	50–100
Simulation Time	T_s	300 ms
Noise Power	N_0	−95 dBm
Repetitions per Scenario	R	5
Total Episodes	E	100

Performance Metrics: Performance of the proposed Wi-Fi 7 architecture is measured in terms of throughput, latency, energy efficiency, and interference minimization.

Throughput

Throughput is how much data can be sent over the network in one second. It is measured in Megabits per second (Mbps). If the throughput is high that means the network is working well. That's why Increased the throughput of wi-fi 7 network means this will make the network work efficiently. [10], [15], [20]

$$\mathrm{T} = \sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{B_i} \log(1 + \mathrm{SINR_i}) \tag{3}$$

The network throughput T, measured in Mbps, represents the total data successfully transmitted over the Wi-Fi 7 network. N denotes the no. of active users connected to the network. B_i show the amount of bandwidth assigned to the i^{th} user in MHz, and $SNIR_i$ is the Signal-to-Interference-plus-Noise Ratio experienced by i^{th} user. These parameters are used to evaluate the overall performance of the proposed Wi-Fi 7 network.

Latency

Latency refers to the amount of time required by the packet of data to be transferred from the source to the receiver. It is denoted in millisecond. The reduced latency ensures better communication performance. [3], [8], [20]

$$L = t_{arrival} - t_{sent} \tag{4}$$

Here L is Network latency and ($t_{arrival}$) is Packet arrival time and (t_{sent}) is Packet transmission time.

Energy Efficiency

The energy efficiency refers to the amount of data transferred via the network per unit of consumed energy. It is denoted in (bits/J). [5], [11], [31]

$$EE = \frac{T}{P} \tag{5}$$

(EE) is Energy efficiency **(**bits/J), (T) represents the Throughput **(Mbps)**, and (P) represents Power consumption (**j**)

Interference Reduction

The percentage of the reduction in network interference in using optimization techniques is referred to as interference reduction. The units of measurement of interference reduction is percent (%). High interference reduction implies efficient spectrum utilization and reliable communications. [17], [24], [27], [33]

$$IR\% = \frac{(I_{before} - I_{after)} \times 100}{I_{before}} \tag{6}$$

(IR) is denoted as Interference reduction (**%**), (I_{before}) is Interference before optimization (**dBm**) and (I_{after}) is Interference after optimization (**dBm**).

IV. Problem Formulation

Despite the advanced capabilities offered by Wi-Fi 7, the increased density and dynamism of the ussers in terms of traffic pose some challenges in the allocation of resources, management of interference, and energy utilization. The baseline Wi-Fi 7 networks do not adjust well to the changing environments of the networks resulting in low throughput and latency. Thus, an adaptive optimization model to control the network resources is required.

This research seeks to develop an adaptive Q-learning based Wi-Fi 7 network model with Multi-Link Operation (MLO), Target Wake Time (TWT), and Channel Puncturing.

Objective Function: The objective function of the proposed dynamic Wi-Fi 7 optimization framework is to maximize throughput, energy efficiency, and interference reduction while minimizing network latency in high-density wireless environments. This is achieved through Q-learning-based adaptive optimization of Multi-Link Operation (MLO), Target Wake Time (TWT), and Channel Puncturing.

Maximize:

$$max(T, EE, IR)$$

Minimize:

$$min(L)$$

T = Throughput (Mbps), EE is Energy Efficiency Mbps/W, IR denotes the Interference Reduction (%) and L is Latency (ms).

V. Proposed Methodology

A Q-learning-based proposed dynamic Wi-Fi 7 architecture is proposed in the suggested methodology in order to boost the performance of networks in dense wireless environments. The architecture combines Multi-Link Operation (MLO) in 2.4 GHz, 5 GHz and 6 GHz spectrum bands along with Target Wake Time (TWT) and Channel Puncturing to realize high throughput, low latency, energy-efficient, and interference-free operations.

Q-learning algorithm follows the bellow mentioned Bellman equation to update the Q-table:

$$Q(s,a) \leftarrow Q(s,a) + \alpha[R + \gamma maxa'Q(s',a') - Q(s,a)] \tag{7}$$

In the proposed Q-learning algorithm, the value of learning rate α = 0.1 is selected, which specifies how much the new information affects the Q-value, and the discount factor γ = 0.95 is the one that shows how important the future reward is. The reward (r) represents the immediate feedback after an action, s denotes the current state of the Wi-Fi 7 network, and s′ represents the next state after the action. The Q-table is updated iteratively, enabling the agent to learn the optimal policy and adapt to changing network conditions over time.

State Space: State space contains all possible network states that could be encountered by the Q-learning agent prior to choosing an action. For the proposed work, state space will be defined by two variables which are network load (low, medium, high) and interference level (low, medium, high). There would be 9 possible states (S0-S8). The Q-learning robot acts according to the current state of the network and its behavior is guided by optimal actions which lead to maximizing throughput, minimizing latency, energy efficiency, and interference in the Wi-Fi 7 network.

Action Selection: Three actions have been chosen for the proposed Q-learning model MLO, TWT, and Channel Puncturing. At each decision-making point, the selects the action with the largest Q-value with respect to the network state. Such actions will ensure that network throughput is maximized, latency reduced, energy efficiency is enhanced, and interference minimized in the dense Wi-Fi 7 environment.

$$A = \{a_1, a_2, a_3\}$$

a_1: MLO, a_2: TWT, a_3: Channel puncturing

Reward Calculation: Following every action that the Q-learning agent takes, the environment performs an evaluation of the network performance. Reward is assigned to aid in the learning process. The reward function is defined in such a way that it aims at maximizing throughput, energy efficiency, and interference reduction while minimizing latency. It is formulated as follows:

$$\boldsymbol{R = w_1T + w_2EE + w_3IR - w_4L} \tag{8}$$

R is the reward function. where T is the throughput, EE is the energy efficiency, IR is the interference reduction, L is the latency, and w_1, w_2, w_3, w_4 are weighting coefficients that determine the contribution of each performance metric. Q-learning algorithm updates Q-table using this reward function to learn optimal resource management policy.

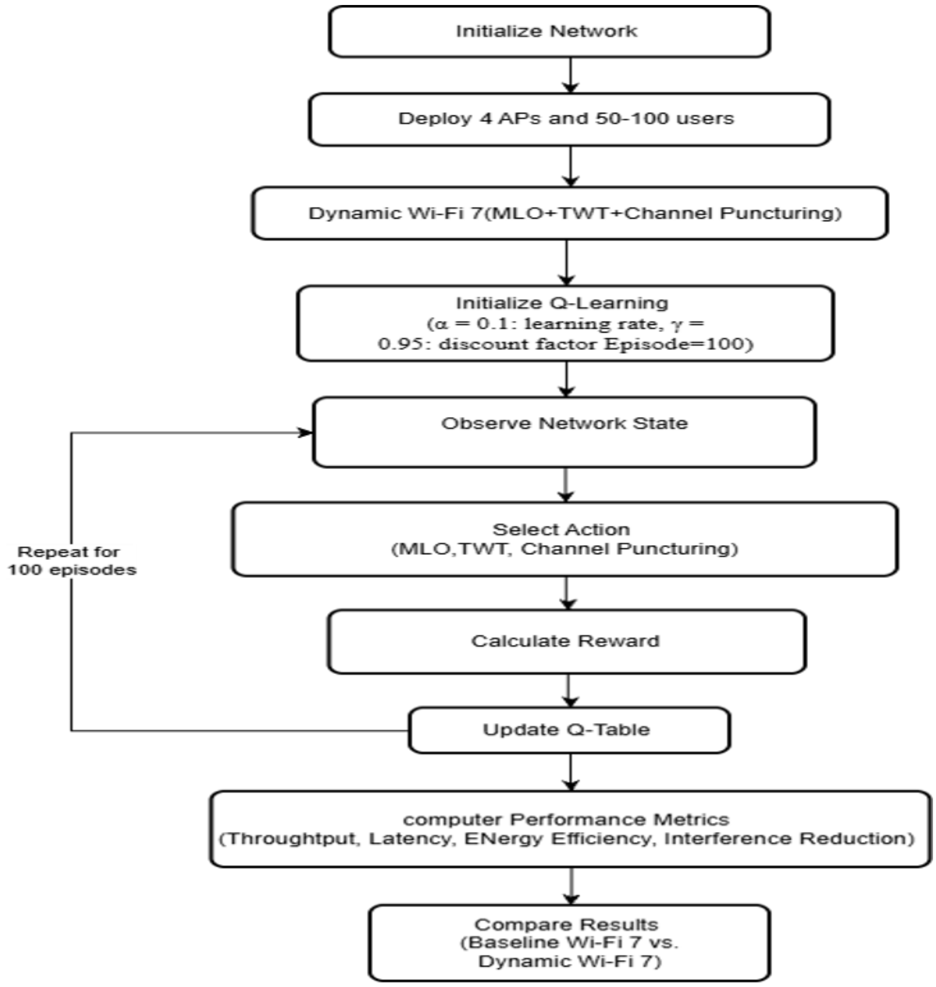

Figure 2: Flow chart of proposed Wi-Fi 7

Algorithm1: Proposed Dynamic Wi-Fi 7 using Q-Learning
Initialize Dynamic Wi-Fi 7 network.
Initialize Q-table with zeros.
Set α = 0.1 and γ = 0.95.
Train the Q-learning agent.
Enable:
• Multi-Link Operation (2.4 GHz + 5 GHz + 6 GHz)
• Target Wake Time (TWT)
• Channel Puncturing
For episode = 1 to 100 do
Generate 50–100 users.
Observe the current network state.
Select the best action from the Q-table.
Allocate the optimal communication link.
Generate dynamic SINR.
Calculate throughput.
Calculate latency.
Measure interference before transmission.
Measure interference after optimization.
Calculate energy efficiency.
Calculate interference reduction.
Update network statistics.
Compute average values for all metrics.
Store episode results.
Display performance graphs.
End

Algorithm 2: Baseline Wi-Fi 7
Initialize network parameters.
Set bandwidth = 320 MHz.
Enable Multi-Link Operation (MLO) using 2.4 GHz and 5 GHz bands.
Set transmission power = 100 W.
For episode = 1 to 100 do
Generate 50–100 users.
For each user do
i. Generate SINR.
ii. Calculate throughput.
iii. Calculate latency.
iv. Measure interference before transmission.
v. Measure interference after transmission.
vi. Calculate energy efficiency.
vii. Calculate interference reduction.
Compute average values for all metrics.
Store episode results.
Plot performance metrics.
End

VI. Simulation Setup

Libraries Employed: For the purposes of the simulation, such libraries were used as NumPy for the purpose of numerical computing, Pandas for data analysis and storing the results, Matplotlib for creating plots, and Random for creating dynamic network environments. The modules employed included Network Environment, Q-Learning Agent, and Train Agent for modeling network environment, Q-Learning algorithm implementation, and training of the agent, respectively.

Programming Language Used: The simulation was developed using Python 3.11.

Hardware Configuration: The proposed Q-learning based Wi-Fi 7 optimization framework was simulated on a computer operating with Windows 11 operating system. The hardware specifications included 11th Gen Intel® Core™ i5-1135G7 CPU @ 2.40GHz processor with 8GB of RAM and Intel® Iris® Xe Graphics (128 MB), and 238 GB SSD.

VII. Results And Discussion

Throughput Analysis: Figure 3 depicts the throughput performance of baseline and Dynamic Wi-Fi 7 frameworks. The proposed framework has achieved the throughput of 1000-1048 Mbps, whereas the throughput of 780-845 Mbps has been accomplished by the baseline framework; this means it is 25%-28% better than the baseline framework. It should be noted that the Q-learning algorithm makes use of the best channels of communication at 2.4 GHz, 5 GHz, and 6 GHz frequencies.

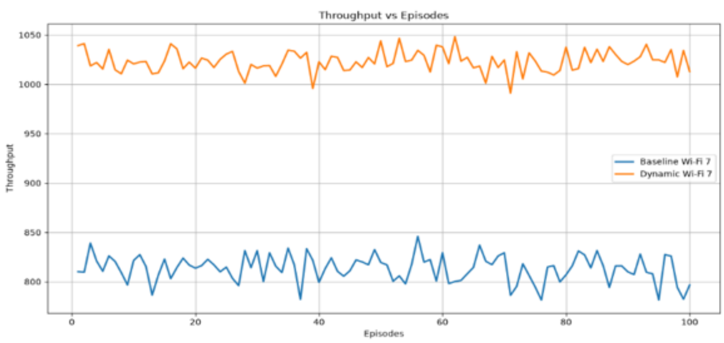

Figure 3: Throughput vs Episodes

Latency Analysis: Figure 4 describes the latency performance for both the baseline and proposed frameworks. The latency has been decreased from 37-43 ms in the baseline framework to 20-25 ms in the Dynamic Wi-Fi 7 framework; this is a reduction of 45%-50%. Using adaptive traffic scheduling, intelligent link selection, and wake up scheduling packet delivery is made efficient in dense wireless network.

Figure 4: Latency vs Episodes

Energy Efficiency Analysis: Energy efficiency analysis outcomes are presented in Figure 5. Energy efficiency of the proposed scheme is within the range from 10.0-10.5 bits/J, while energy efficiency of the traditional scheme equals 7.8-8.4 bits/J. That means that the improvement rate is about 25-30%. Using TWT and Q-learning allows preventing unnecessary transmissions and listening, so there is no need for energy, but throughput remains at its usual level.

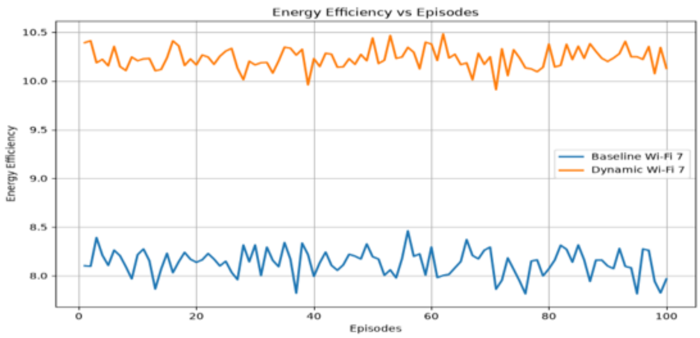

Figure 5: Energy Efficiency vs Episodes

Interference Reduction Analysis: The performance evaluation results with respect to interference reduction of both the frameworks are provided in Figure 6. The interference reduction rate of the Dynamic Wi-Fi 7 framework is 60-65%, but interference reduction of the baseline framework is 20-24%, which means three times more interference reduction rate has been achieved by using the proposed scheme. Such a high level of improvement is mainly due to adaptive channel selection and Channel Puncturing.

Figure 6: Interference Reduction vs Episodes

Table 3: Comparative Summary

Performance Metric	Baseline Wi-Fi 7	Proposed Dynamic Wi-Fi 7	Improvement
Throughput (Mbps)	780-845	1000-1048	25–28%
Latency (ms)	37-43	20-25	45–50%
Energy Efficiency(bits/J)	7.8-8.4	10.0-10.5	25–30%
Interference Reduction (%)	20-24	60-65	Nearly 3×

VIII. Conclusion

The paper proposes a Q-learning-based Wi-Fi 7 optimization technique for high density wireless networks. The presented optimization framework provides increased throughput and energy efficiency and decreased latency and interference during intelligent resources management with MLO, TWT, and Channel Puncturing. The results show the possibility of effective Wi-Fi 7 network performance optimization with the help of reinforcement learning.

Future Work:

The next stage of development of the proposed Wi-Fi 7 framework will be to replace Q-learning with the more modern Deep Reinforcement Learning (DRL) methods, for example, Deep Q-Networks (DQN). Moreover, the Wi-Fi 7 framework can be tested in the context of ultra-dense Wi-Fi 7 networks where there will be many more users and access points than those considered in the current work.

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