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Performance Evaluation of Optimized IEEE 802.11ax in IIoT Environments: Throughput, Latency, and Packet Loss Improvements

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ABSTRACT

This paper presents a comprehensive performance evaluation of optimized IEEE 802.11ax networks in Industrial Internet of Things (IIoT) environments focusing on three critical performance metrics: throughput, latency, and packet loss. Using a Deep Reinforcement Learning (DRL)-based optimization strategy, the researchers configured MAC layer parameters to meet the demands of heterogeneous industrial traffic demands. Justification for the use of DRL is provided by its ability to handle complex, stochastic environments effectively. MATLAB simulations modelled and analyzed network performance under harsh IIoT environments, characterized by electromagnetic interference (EMI), fluctuating traffic loads, high-density device deployments, and significant physical obstructions such as metal structures. The results showed that the optimized network significantly improved system throughput, average transmission delay, and packet retransmission rate. The peak throughput increased from 1420 Mbps to 2150 Mbps, and the highest packet loss ratio decreased from 32.5% to 23%. Latency also saw notable improvement, with the number of nodes experiencing latency greater than 0.1 seconds decreased from 5 to 1. These findings demonstrated that the proposed optimization strategy for IEEE 802.11ax systems can significantly enhance performance in IIoT environments, making them more reliable and efficient for industrial applications.

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1. Introduction

Industrial Internet of Things (IIoT) is a transformative technological concept that integrates traditional industrial systems with advanced technologies such as sensors, cloud computing, and data analytics to create a more efficient and interconnected industrial ecosystem. As a result, IIoT has the potential to revolutionize various industries such as manufacturing, energy, healthcare, and transportation by enabling real-time monitoring, automation, and predictive maintenance (Arnold et al., 2022). According to a study by Jain et al. (2021), IIoT can improve overall equipment effectiveness, reduce downtime, optimize asset utilization, and enhance supply chain management in manufacturing industries. IIoT also plays a crucial role in the energy sector by facilitating the deployment of smart grids, demand response systems, and energy management solutions. A study conducted by Pedro (2021) demonstrates that IIoT-based applications provide real-time visibility into energy usage patterns, enable energy conservation, and support the integration of renewable energy sources. These findings underscore the importance of IIoT in creating a more sustainable and efficient energy infrastructure.

The success of IIoT heavily relies on robust and efficient communication protocols to facilitate seamless data transfer and real-time decision-making (Goudarzi et al., 2021). Introduced to overcome the limitations of its predecessor, IEEE 802.11ax protocol was designed to provide higher data rates, increased capacity, and improved performance (Wilhelmi et al., 2021), making it particularly relevant for IIOT applications where a multitude of devices coexist in a dynamic and challenging environment.

IEEE 802.11ax, also known as Wi-Fi 6, is a wireless communication standard with improved performance and efficiency. It builds upon the features of its predecessor, IEEE 802.11ac (Wi-Fi 5), and introduces enhancements to address the growing demands of modern wireless communication.

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The origins of 802.11 date back to the 1980s when the Federal Communications Commission (FCC) opened up the Industrial, Scientific and Medical (ISM) radio bands for commercial applications (Pahlavan & Krishnamurthy, 2021). This led to early research in the 1990s on wireless local area networks (WLANs) technologies by companies and academic institutions. In 1997, the first 802.11 standard was ratified by the Institute of Electrical and Electronics Engineers (IEEE) which defined 1 Mbps and 2 Mbps data rates based on frequency hopping or direct sequence spread spectrum in the 2.4GHz ISM band. 802.11a operated in the 5GHz band for reduced interference providing up to 54 Mbps speeds using OFDM (Pahlavan & Krishnamurthy, 2021)

Over the 2000s, further amendments to 802.11 were developed and ratified to enhance the capabilities of WiFi. 802.11b achieved speeds up to 11 Mbps by introducing CCK modulation. Then high throughput 802.11n with features like MIMO and wider bandwidth brought significant performance gains hitting 600 Mbps (Gast, 2012). This rapid evolution continued into the 2010s with 'VHT' 802.11ac reaching up to 6.9 Gbps speeds through 256-QAM, 8 spatial streams and 160 MHz channels. Most recently, 802.11ax or Wi-Fi 6 focuses on improving efficiency, density support and latency rather than peak data rates (Khorov et al., 2020).

2. Materials and Methods

2.1. Research Design

The design incorporated several key stages, including the selection of appropriate simulation tools, IIoT environment modeling, parameter initialization, and optimization of network variables using DRL. The network was then analyzed for performance in both 'unoptimized' state and optimized state focusing on throughput, latency and packet loss. Fig. 1 is a flow chart giving a summary of the Research Design.

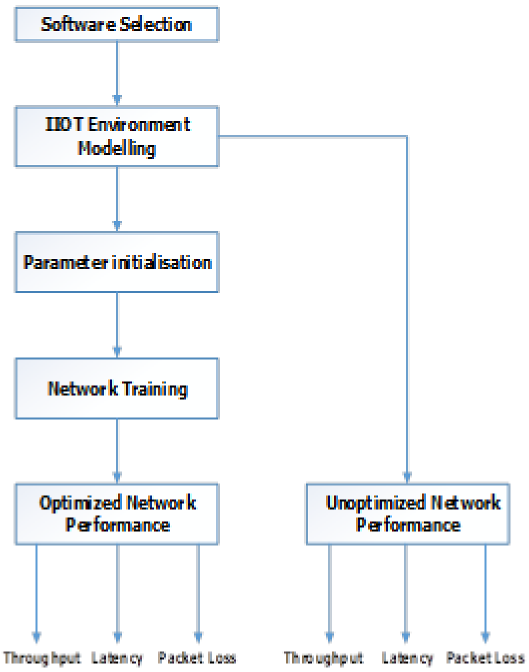

Fig. 1: Research Design Flow Chart

It is important to note that simulated environments do not fully replicate real-world industrial settings. However, they provide valuable insights into network behavior under controlled conditions and allow for performance comparisons between optimized and unoptimized states. (Lee et al., 2023)

2.2. Software selection

MATLAB 2024a was selected for this project due to its versatility in handling various aspects, including simulation, optimization, and deep reinforcement learning. Its matrix-based language provided an intuitive way to express mathematical computations, while built-in graphics capabilities enabled easy visualization and extraction of insights from data

The WLAN Toolbox™ and Communications Toolbox™ were crucial components of the simulation setup. The toolboxes offered functions for designing, simulating, analyzing, and testing WLAN communication systems. To enhance the deep learning capabilities, Python libraries were integrated into MATLAB. This integration allowed the project to harness Python's libraries, providing access to advanced model architectures, optimizers, and pre-trained models without rebuilding them from scratch in MATLAB.

2.3. IIoT Environment Modelling in Matlab software

A key focus of this research is performance optimization in harsh factory environments. The term harsh in this context refers to an IIoT environment characterized by:

High levels of electromagnetic interference (EMI) from industrial machinery, which disrupts wireless communication.
Dense network deployments leading to channel congestion and increased packet collisions.
Physical obstructions, such as metal enclosures and factory equipment, causing severe signal attenuation.
Fluctuating traffic loads, requiring dynamic adaptation of network parameters.
Environmental challenges, including temperature variations and dust interference, impacting device performance (Jasperneite et al., 2020).

Given these challenges, optimizing IEEE 802.11ax performance in such conditions is crucial to ensuring reliable, low-latency, and high-throughput communication in IIoT applications. To mimic IIoT environment in MATLAB, various tools and features provided by MATLAB and its toolboxes were utilized.

Interference was modeled using stochastic processes to simulate real-world industrial environments by Eq. 1.

$$I(t) = \sum_{k=1}^{N_I} p_k^i . e^{j2\pi f_k t} \quad (1)$$

Where $I(t)$ is the interference signal, P_k is the power of the k^{th} interfering signal, and N_I N_I is the number of interfering signals.

Wall models were incorporated into simulation environment to account for signal attenuation, reflections, and interference caused by the walls. Different properties of walls, such as material, thickness, and positions, were defined using the appropriate functions and objects in the toolbox. A system with 81 nodes was created, where the first 27 nodes represented Access Points (APs) and the remaining 54 nodes represented Stations (STAs). MATLAB's built-in data structures (e.g., structs or classes) was used to define the properties and behaviors of each node, such as transmit power, receiver sensitivity, and communication protocols. The provided helper function hGetIDsAndPositions was used to obtain the IDs and random positions for the APs a/nd STAs within each room. The node IDs, AP positions, and STA positions were stored in MATLAB variables or data structures for later use in the simulation.5 STAs in each room were Associated to the corresponding AP by using the associateStations object function of the wlanNode object. APs then configured with continuous application traffic to their associated STAs using the FullBufferTraffic argument.

Fading channel models were applied to the wireless links between the Aps and STAs, taking into account factors like distance, obstacles, and interference. The simulation considered both Rayleigh and Rician fading models to reflect varying IIoT conditions. The Rayleigh model was applied to non-line-of-sight (NLOS) transmissions, while Rician fading was used for line-of-sight (LOS) scenarios, ensuring realistic channel behavior representation.

The mathematical representation of the fading channel is given in Eq. 2. Where hLOS and hNLOS are the line-of-sight and non-line-of-sight components, respectively.

$$h(t) = \sqrt{½(hLOS + hNLOS)} \tag{2}$$

The line-of-sight component hLOS accounts for the direct signal path between the transmitter and receiver, while the non-line-of-sight component hNLOS includes reflected, scattered, and diffracted signals caused by obstacles. The Rayleigh fading model assumes no line-of-sight path, while the Rician fading model incorporates both line-of-sight and scattered paths, with the Rician K-factor indicating the ratio of power in the direct path to the power in the scattered paths. (Ciezobka et al., 2023).

DRL was selected for this study due to its superior ability to optimize decision-making in stochastic environments where conventional static models fail. Unlike heuristic approaches, DRL continuously learns and adapts to variations in industrial network conditions, optimizing contention window sizes, transmission power, and frame aggregation dynamically. Its suitability is validated through extensive literature, such as (Goudarzi et al., 2023) which demonstrated its effectiveness in wireless time-sensitive networking.

2.4. Initialization of Optimisation Parameters

The selection of parameters for the simulation, such as the simulation time, modulation and coding scheme (MCS), and transmission power was based on IEEE 802.11 ax standard. Simulation time was set at 12 seconds. Short simulation times can be useful for quickly evaluating the system's performance, testing different configurations, or analyzing transient behaviors. The wlanDeviceConfig function in MATLAB's Wireless Communications Toolbox was used to configure the properties of wireless devices in a WLAN simulation. Two configuration objects were created: one for Access Points (APs) and another for Stations (STAs).

2.5. Network Training

The network training process for DRL model was a crucial step in optimizing the IEEE 802.11ax network's performance. The primary objective of this training was to enable the network to learn from data and adjust the protocol parameters dynamically to meet the application requirements. In order to define the optimization problem, an objective function which represents key performance indicators such as throughput, latency, or packet retransmission rate was denoted as $J(\theta)$ (Eq. 3) where θ represents the parameters to be optimized (that is contention window size, transmission power, frame aggregation). The goal was to minimize the delay D or maximize the throughput T; therefore, the objective function was expressed as shown in Eq. 3.

$$J(\theta) = Maximize[T(\theta) - \alpha D(\theta)] \tag{3}$$

Where α is a weighting factor balancing throughput and delay. The inclusion of delay subtraction from throughput is derived from weighted optimization principles, ensuring latency-sensitive traffic is prioritized.

During the training process, forward propagation is performed, where the input data was passed through the neural network to obtain the expected value of the loss function. The loss function is designed to capture the performance metrics of interest, such as system throughput, delay, and packet retransmission rate. By incorporating these metrics, the network could learn to optimize the protocol parameters to improve the overall network performance.

After obtaining the expected value of the loss function, the error terms for the output and hidden layers were calculated. These error terms quantify the difference between the network's predictions and the desired outputs. Subsequently, the gradient values of the loss function with respect to the connection weights and bias terms were determined using backpropagation techniques.

3. Results

3.1. Baseline Performance of Unoptimized 802.11ax Network

3.1.1. Throughput

In the "Throughput at Each node" plot, Fig. 2, the x-axis represented the nodes and the y-axis represented the throughput in Mbps. It was observed that throughput varied significantly across different APs, with some APs achieving high throughput (e.g., AP7 at 1420 Mbps) while others had zero throughput (e.g., AP3, AP23, AP25). This variability highlights the challenges in ensuring consistent performance across the network, likely due to factors such as interference, node placement, and traffic load.

Mean (594Mbps): This represents the average of all values. It's lower than the expected value because of the presence of several low values, including three zeros.
Mode (180Mbps): This indicates the most common value in the dataset. This represents a common baseline in throughput measurement.
Median (630Mbps): This was the middle value when the data was sorted. It was higher than the mean, which suggests that the distribution was slightly skewed towards lower values.

The difference between the mean and median (median being higher) indicates that the distribution was not symmetrical, but rather skewed to the left (negatively skewed). This is further supported by the presence of a few high values (like 1350 and 1420) which pulled the mean up, but not as much as the low values pulled it down. The mode being much lower than both the mean and median suggests that while 1.8 is the most common value, there are many higher values that influence the overall distribution. This kind of distribution indicated that throughput measurement had a common low value, but also the potential for significantly higher readings in some cases.

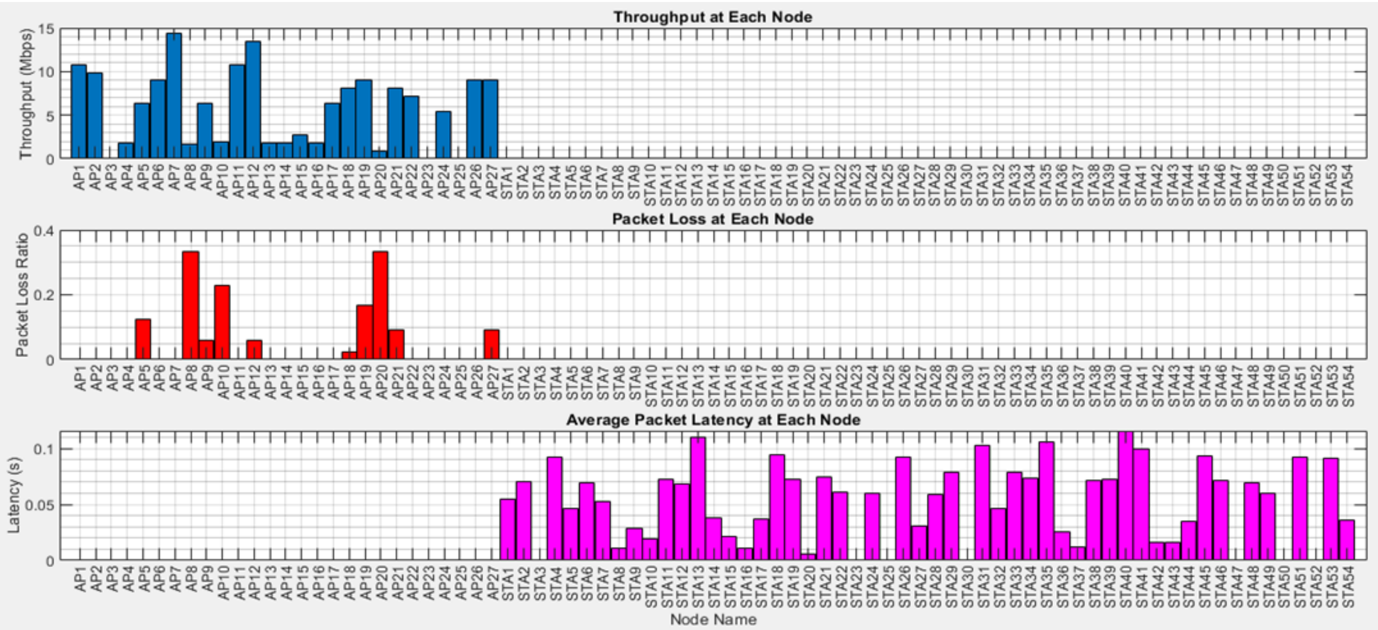

Fig. 2: Throughput, packet loss ratio and latency in unoptimised network.

3.1.2. Packet Loss

In the "Packet Loss at Each Node" plot, Fig. 2, the x-axis represents the nodes, and the y-axis represents the packet loss ratio. The data reveals significant insights into the network's performance and areas needing improvement. The following basic statistics were observed:

2 nodes (8.3%) had very high packet loss (>30%): 32.5% each.
1 node (4.2%) had high packet loss (20-30%): 23%.
2 nodes (8.3%) had moderate packet loss (10-20%): 16.5% and 12.5%.
5 nodes (20.8%) had low packet loss (<10%): 9%, 9%, 6%, 6%, and 2%.
Mean packet loss: 6.23%.
Median packet loss: 0%.

Nodes AP8 and AP20 exhibit a high packet loss of 32.5%, indicating severe issues and could lead to underperformance in the network. Additionally, nodes like AP3, AP23, and AP25 showed zero packet loss but also zero throughput, indicating no active data transmission.

There was a cluster of higher packet loss nodes at the beginning of the list, suggesting that certain areas or types of nodes might be more prone to packet loss. While more than half of the nodes performed optimally with no packet loss, the presence of nodes with high packet loss percentages indicates significant room for improvement in network reliability. Nodes with zero packet loss (AP1, AP2, AP6, AP7, AP11, AP13, AP14, AP15, AP16, AP17, and AP22) suggest good network performance.

3.1.3. Latency

STA3, STA23, STA25, STA30, STA50, and STA52 showed zero latency. These STAs were associated with AP3, AP23, and AP25. Zero latency in this context indicated no active data transmission, hence no measurable delay. Five nodes experienced latency greater than 0.1 seconds. High latency indicates delays in data transmission, which negatively impacted network performance.

3.2. Performance of Optimised 802.11ax Network

3.2.1. *Throughput*

The mean increased significantly from 595Mbps to 829Mbps, indicating a general improvement in performance. This suggests that the optimization raised the overall average throughput by 39%.

Mode: The mode shifted from 180Mbps to 960Mbps, which was a substantial improvement. This indicates that the most common performance level has increased dramatically, suggesting more consistent higher throughput performance.

Median: The median increased from 630 to 710. This shows that the middle value of the dataset has improved, indicating a general upward shift in throughput across the board.

Range and Distribution: The range has expanded, with both the minimum and maximum values increasing. The elimination of zero values suggests that all nodes are actively participating in data transmission, indicating a more stable and optimized network. The improved balance across the network demonstrates better load distribution, reducing bottlenecks and enhancing overall system efficiency.

The optimized state still shows significant variability, but with a higher baseline. The spread of values is more even in the optimized state, without the cluster of very low values seen in the 'unoptimized' state. The optimized state showed improvements across all key metrics (mean, mode, median). The lowest performances were elevated (120Mbps vs 0), suggesting that underperforming nodes were improved. The highest performance was increased (2150Mbps vs 1420Mbps), indicating that the optimization also raised the peak capabilities. The optimized state appeared to have more consistent performance, with fewer extreme low values and a higher mode. This suggests that the optimization not only improved performance but also made it more reliable across different nodes or conditions. The optimization process has positively impacted overall network performance. Notably, no nodes exhibited zero throughput. This indicates that all nodes actively participated in data transmission, highlighting the efficiency and effectiveness of the network.

The optimization was successful in improving overall performance, raising the baseline performance, increasing peak performance, and creating more consistent results across the system. The elimination of zero values and the significant increase in the mode suggest that previously underperforming elements have been substantially improved. The optimization resulted in a more balanced and slightly better-performing network overall, with significant improvements in the worst-case scenarios.

3.2.2. *Packet loss*

The highest packet loss was reduced by 29.2%, indicating improvement in the worst-performing nodes. The overall average packet loss was decreased by 19.7%, showing a general improvement in network performance. While the median was slightly increased, this was due to a more even distribution of packet loss across nodes. The packet loss was more evenly distributed in the optimized state, avoiding extreme values seen in the 'unoptimized' state.

3.2.3. *Packet Latency*

Latency in optimized IEEE 802.11ax was plotted as shown in Fig. 3. Unlike in 'unoptimized' network where five nodes experienced latency greater than 0.1 seconds, in Optimized network only one node experienced latency greater than 0.1 seconds. The overall latency across the network decreased significantly. This improvement indicates more efficient data transmission and better handling of network traffic.

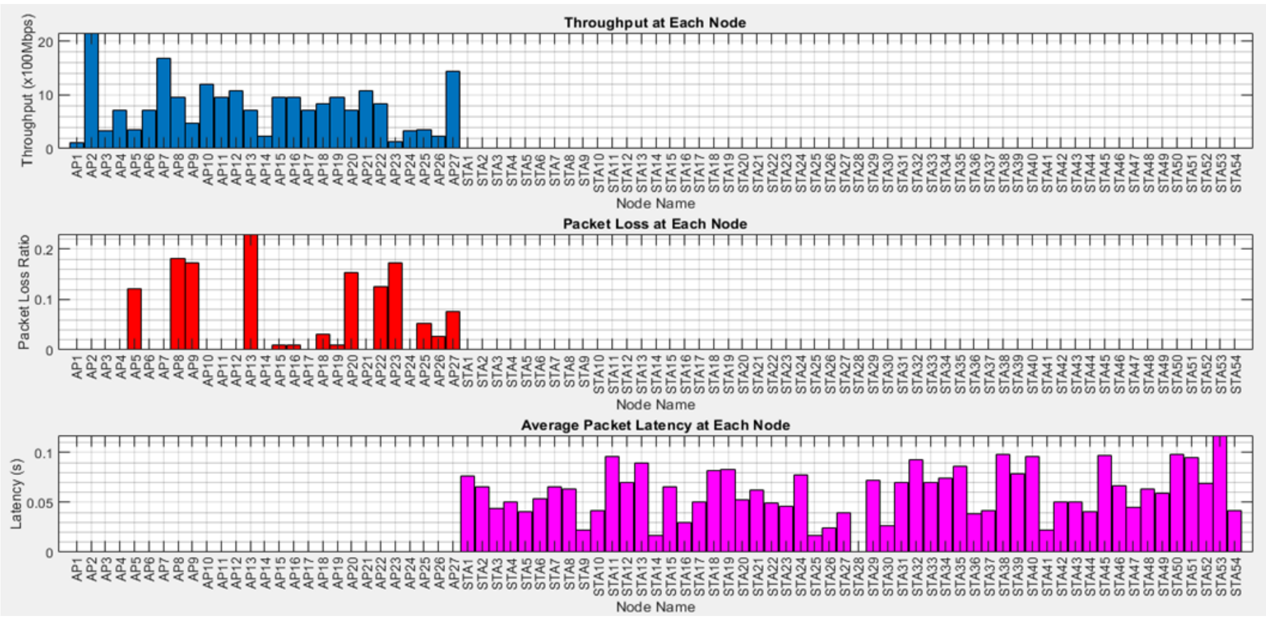

Fig. 3: Throughput, packet loss ratio and latency in optimized network.

4. Discussion

The IEEE 802.11ax standard specifies a maximum theoretical data rate of 9.6 Gbps for 8 spatial streams and 2.5 Gbps for 2 spatial streams (Khorov, Kiryanov, & Krotov, 2019).

The highest throughput achieved in this study was 2150 Mbps (2.15 Gbps) by AP2. This was higher than the maximum achievable theoretical throughput for IEEE 802.11b, IEEE 802.11a, IEEE 802.11g, and IEEE 802.11n. While the observed throughput is lower than the theoretical maximum in IEEE 802.11ax and IEEE 802.11ac, it's important to note that the theoretical maximum is rarely achieved in practical scenarios due to various overheads and real-world limitations. According to Bellalta & Kosek-Szott, (2019) actual throughput in Wi-Fi networks typically ranges from 50-70% of the theoretical maximum due to protocol overheads, channel conditions, and inter-user interference. Maximum achieved throughput in this study was 2.15 Gbps, representing approximately 86% of the theoretical maximum, which aligns with expectations for real-world deployments, especially considering the complex IIoT environment simulated.

Ali et al. (2018) reported achievable throughputs of up to 1.9 Gbps in their experimental study of 802.11ax and 802.11ac in industrial environments which 2.15Gbps results in this study surpass, indicating successful optimization.

IEEE 802.11ax targets low latency, typically under 10ms for less dense network applications (Qu et al., 2019). Optimized network in this study, most nodes showed latency below 0.1 seconds (100ms), with only one node exceeding this threshold. While not achieving the ideal sub-10ms latency across all nodes, this represents a significant improvement from the 'unoptimized' network. The latency performance aligned well with the observations of Saha & Dhillon, (2019), who reported latencies between 20-250ms in their study of 802.11ax in dense IoT scenarios. The majority of nodes meeting low latency requirements indicates a successful optimization in line with the standard's goals and practical expectations for IIoT environments.

For most wireless applications, a packet loss rate below 1% is considered good, while anything above 2-3% may start to impact performance noticeably (Jain et al., 2021). In this optimized network, the highest packet loss ratio was 23%. According to Khorov, Kiryanov et al. (2019), Wi-Fi 6 targets a packet error rate (PER) of less than 1% for most applications. The maximum packet loss in optimized network (23%) was slightly higher than the Wi-Fi 6 target. However, it's worth noting that Wi-Fi 6 performance can vary greatly depending on environmental factors and network congestion. In Bellalta & Kosek-Szott (2019), researchers suggested that in real-world scenarios, packet loss rates for Wi-Fi networks can range from 1% to 20% depending on the environment and network load.

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