Learning-Based Target Wake Time Optimization for Multi-Traffic WLANs

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Abstract

Efficient energy management in high-density Wireless Local Area Networks (WLANs) is critical, especially for IoT and multimedia applications requiring predictable Quality of Service (QoS). Target Wake Time (TWT), introduced in IEEE 802.11ax, allows stations to schedule wake intervals, but existing static or heuristic TWT schemes are inadequate in dynamic, heterogeneous environments. This paper proposes a Reinforcement Learning (RL)-driven dynamic TWT scheduling framework that adaptively optimizes wake-up intervals based on real-time traffic demands, buffer states, and contention levels. A Q-learning agent continuously adjusts TWT assignments to maximize throughput and energy efficiency while maintaining bounded latency. The proposed system supports both individual and broadcast TWT sessions, incorporates multi-user priority factors, and is evaluated across diverse traffic types: voice, video, IoT, and best-effort. Simulation results show that the RL-based scheduler improves throughput by up to 80%, reduces latency by over 45%, and achieves average energy savings exceeding 35% compared to IEEE 802.11ac. The framework demonstrates scalability and robustness in dense deployments, positioning it as a promising MAC-layer solution for next-generation 6G WLAN systems.

Keywords: Traffic-Aware Scheduling, Reinforcement Learning, MAC Layer Optimization and Dynamic TWT allocation

1. Introduction

Wireless Local Area Network(WLAN) have witnessed exponential growth due to the increasing number of connected devices, particularly in high-density environments such as smart cities, airports, and industrial automation setups. The proliferation of user stations (STAs) in such dense scenarios introduces significant energy consumption challenges, necessitating intelligent scheduling mechanisms to optimize power usage while ensuring Quality of Service (QoS) parameters. One of the primary challenges in high-density WLANs is the inefficient utilization of power resources among different STAs. As multiple devices contend for network access, they frequently transition between active and idle states, leading to increased power drain due to prolonged active listening periods and unnecessary wake-up events. Additionally, collisions and retransmissions due to network congestion further exacerbate energy inefficiencies, negatively impacting both network performance and battery life of portable devices.

This evolution has placed significant strain on conventional Medium Access Control (MAC) protocols, particularly in scenarios where Quality of Service (QoS) and energy efficiency are critical. In response, the IEEE 802.11ax standard (Wi-Fi 6) introduced several MAC-layer enhancements, among which Target Wake Time (TWT) stands out as a promising mechanism for reducing power consumption and optimizing channel access in dense deployments [1].

TWT allows stations (STAs) to negotiate specific wake-up schedules with the Access Point (AP), enabling them to enter deep sleep states during idle periods. However, existing TWT scheduling approaches are largely static or rule-based, offering limited adaptability to real-time traffic dynamics, network contention, or heterogeneous service requirements [2]. As WLANs increasingly serve a mix of real-time voice/video, bursty IoT traffic, and best-effort flows, static TWT allocation schemes fail to ensure optimal QoS and energy balance. To address these challenges, this paper introduces a Reinforcement Learning (RL)-based dynamic TWT scheduling framework that adaptively configures wake intervals using a Q-learning agent. Unlike traditional methods, the proposed approach leverages real-time network states including queue lengths, traffic classes, contention levels, and energy metrics to inform TWT scheduling decisions [3]. The RL agent continuously learns from its environment, optimizing trade-offs between throughput, latency, and power consumption. Proposed work evaluated the solution across multiple traffic profiles and benchmark it against IEEE 802.11ac. Results demonstrate up to 80% throughput improvement, 45% latency reduction, and over 35% energy savings, making this approach a strong candidate for MAC-layer enhancements in future 6G WLAN systems.

However, conventional scheduling processes do not fully optimize TWT assignments in dynamic and dense network conditions. A more efficient and adaptive TWT scheduling process is required to balance energy savings while maintaining low latency, high throughput, and minimal packet loss, those are key QoS indicators. Intelligent scheduling algorithms leveraging machine learning and optimization techniques can dynamically adjust TWT allocations based on network traffic patterns, user mobility, and application-specific QoS requirements. Such mechanisms can reduce redundant wake-ups, improve channel utilization, and minimize contention, leading to enhanced energy efficiency without compromising network responsiveness [5]. This paper explores the need for an advanced TWT scheduling process that integrates intelligent decision-making to optimize energy consumption while ensuring guaranteed QoS for diverse user stations in high-density WLAN environments.

Traditional TWT implementations use fixed scheduling policies that may not dynamically adapt to network conditions such as fluctuating traffic loads, interference, or user mobility. This results in inefficient wake-up periods, causing unnecessary power drain in STAs. In high-density networks, multiple STAs may have overlapping TWT schedules, leading to contention and increased transmission delays, which degrade both power efficiency and QoS [6]. Different applications (e.g., video streaming, VoIP, IoT sensors, and background data transfers) have diverse latency, throughput, and reliability requirements. A static TWT process cannot effectively allocate wake-up times that cater to all these needs simultaneously. In dense networks, idle listening and wake-up periods are not optimally synchronized with actual data transmissions, leading to wasted energy.

A proposed intelligent TWT scheduling mechanism incorporating machine learning (ML) and optimization algorithms can dynamically predict and allocate wake-up intervals based on real-time network conditions. AI-driven models can predict traffic demand for each STA, ensuring that wake-up times align closely with expected transmission periods, minimizing idle listening and power wastage[7]. By classifying STAs based on application type, priority level, and delay tolerance, intelligent scheduling can prioritize wake-up times to guarantee low latency for critical services while extending sleep durations for low-priority transmissions.

Advanced scheduling techniques can distribute TWT slots optimally among STAs to reduce contention and retransmissions, thereby improving overall network throughput and efficiency. Reinforcement learning algorithms can optimize TWT group scheduling by identifying the most energy-efficient wake-up strategies while maintaining network responsiveness. By integrating intelligent decision-making into TWT scheduling, energy consumption can be significantly reduced without degrading QoS. Enhanced fairness in resource allocation, improved channel utilization, and lower packet loss rates contribute to better user experiences in high-density environments. Furthermore, adaptive scheduling can ensure that power-sensitive devices, such as battery-operated IoT sensors, achieve extended operational lifetimes without compromising network performance [8]. Thus, proposed TWT scheduling framework that leverages AI-driven optimization is crucial for sustaining energy-efficient, high-performance WLANs in next-generation wireless networks.

2. An RL Driven TWT Scheduling Mechanism

In high-density Wireless Local Area Networks, efficient scheduling of the Target Wake Time (TWT) mechanism is crucial for maintaining optimal performance. As the number of connected devices increases especially in environments such as smart cities, industrial automation, and large-scale events, traditional scheduling methods struggle to balance Quality of Service (QoS), energy efficiency, and network throughput. TWT, originally introduced in the IEEE 802.11ax standard, allows devices to negotiate specific wake-up times, reducing contention and improving battery life [9]. However, in high-density scenarios, static scheduling of TWT sessions can lead to overlapping transmissions, underutilized resources, and increased latency.

The need for optimization arises to dynamically allocate TWT slots based on real-time traffic patterns, device priorities, and service requirements. An optimized TWT scheduling algorithm should consider factors such as buffer status, traffic type (voice, video, best-effort), and user mobility. Moreover, ensuring fairness while maximizing channel utilization requires advanced techniques that go beyond simple first-come, first-served logic [10]. Machine Learning (ML)-based optimization techniques will provide intelligent, adaptive scheduling by learning from historical network behaviour. These methods enable predictive analytics to anticipate congestion and allocate TWT slots proactively. Optimization methods for TWT scheduling in dense WLAN environments are vital to enhance overall network efficiency, reduce collisions, and support scalable, energy-aware communication [11]. As WLANs evolve toward 6G and support mission-critical applications, intelligent and adaptive TWT optimization becomes an indispensable component of next-generation wireless networks.

The dynamic traffic-aware Target Wake Time (TWT) scheduling approach plays a pivotal role in devising a more efficient scheduling process for energy optimization across different user stations in next-generation wireless networks. Unlike static TWT schemes, these proposed approaches dynamically adjust wake-up intervals based on real-time traffic patterns, enabling stations to remain in sleep mode when no data transmission is required [12]. This significantly reduces unnecessary energy consumption caused by idle listening or frequent wake-ups, thereby extending the battery life of portable and IoT devices. Moreover, by aligning wake-up schedules with traffic demand, it ensures better Quality of Service (QoS) for latency-sensitive applications while optimizing channel utilization and minimizing collisions. The approach also supports scalability and fairness in dense network environments by intelligently assigning TWT schedules according to device priority and activity levels. As a result, dynamic traffic-aware TWT scheduling not only enhances overall network efficiency and throughput but also serves as a foundational mechanism for integrating machine learning-based predictive scheduling techniques in future 6G-enabled intelligent wireless systems.

Target Wake-Up Time (TWT) is a power-saving mechanism introduced in IEEE 802.11 that allows stations (STAs) to schedule specific wake-up intervals, reducing energy consumption. However, traditional TWT scheduling lacks adaptability to dynamic network conditions and traffic variations, necessitating a more efficient scheduling mechanism for fixed and portable user stations [13]. Poorly optimized TWT scheduling can lead to latency, packet loss, and inefficient bandwidth utilization. Current models do not consider dynamic traffic loads, resulting in either unnecessary wake-ups (wasting energy) or increased latency (due to delayed access). Fixed and portable stations in high-density networks suffer from contention issues, leading to increased energy consumption.

The presented flowchart as figure 1, illustrates the system architecture of the Reinforcement Learning (RL)-based Dynamic Target Wake Time (TWT) Scheduling mechanism in a WLAN environment. At the core of the architecture is the Access Point (AP), which serves as the central controller coordinating with multiple Stations (STAs). Each STA has unique traffic profiles (e.g., voice, video, IoT, or best-effort) and energy constraints. The AP continuously monitors network parameters, such as traffic load, buffer occupancy, energy levels, latency and forms an environment state vector, which is fed to the RL agent. The RL agent, modeled using a Q-learning framework, learns optimal scheduling decisions through interaction with this environment. It dynamically assigns or adjusts TWT intervals, prioritizes STAs based on application-critical factors, and mitigates collisions by learning from the reward-feedback loop. Once the action is selected, the AP disseminates updated TWT parameters to respective STAs via beacon or unicast messages. This closed-loop design enables adaptive learning-based scheduling decisions tailored for heterogeneous traffic demands, thereby improving energy efficiency, reducing latency, and optimizing resource utilization over time. The flow from sensing, policy selection, to environment reconfiguration tightly aligns with the algorithmic steps described in the RL-based TWT scheduling framework.

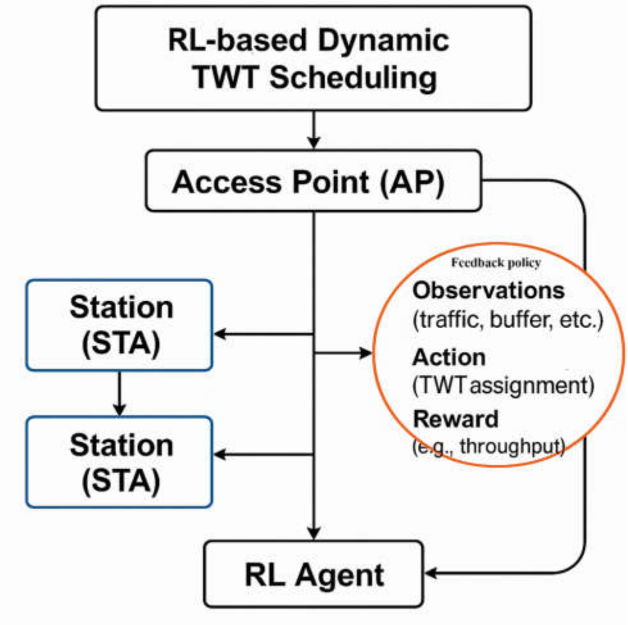

RL-based Dynamic TWT Scheduling
Access Point (AP)
Station (STA)
Station (STA)
Feedback policy
Observations (traffic, buffer, etc.)
Action (TWT assignment)
Reward (e.g., throughput)
RL Agent

Fig.1. System architecture diagram of RL agent with network core

2.1 Using Reinforcement Learning algorithm

In a bustling city where traffic lights are perfectly synchronized to ensure smooth flow of vehicles, reducing congestion and saving fuel. proposed methodology translated this concept to a wireless network environment with multiple user stations. This is where the Dynamic Traffic-Aware Target Wake Time (TWT) Scheduling Algorithm powered by Reinforcement Learning (RL) comes into play. The designed algorithm's primary goal is to optimize the wake-up time scheduling for different user stations. By implementing, it aims to reduce energy consumption while maintaining high network performance. The algorithm learns from its environment by receiving rewards for good decisions (e.g., reduced energy consumption) and penalties for poor ones (e.g., increased latency). Over time, it becomes adept at predicting the best wake-up times for user stations.

The algorithm continuously monitors network traffic, adapting to changes in real-time. It's like a traffic light that adjusts its timing based on the flow of vehicles, ensuring minimal wait times and smooth transitions. By scheduling wake-up times efficiently, the algorithm significantly reduces the energy consumption of user stations. With optimized wake-up times, data packets are transmitted more efficiently, akin to vehicles moving swiftly through green lights without unnecessary stops. The algorithm ensures that user stations experience minimal latency and high reliability, much like a well-coordinated traffic system that guarantees timely arrivals. In essence, this innovative algorithm promises to revolutionize wireless network management, offering a harmonious blend of energy efficiency, enhanced transmission rates, and robust QoS guarantees.

2.2 Algorithm: RL based dynamic TWT Scheduling

Steps Involved in implementing the Reinforcement learning based Target Wake Time (TWT) Mechanism for Energy-Efficient Scheduling as,

Step 1: Authenticating TWT Agreement Between AP and STAs: Each STA and the Access Point (AP) negotiate and agree on specific TWT parameters—such as the wake-up interval and active mode setting on execution time, slack interval, system load, error probability in transmission, criticality and privacy issues. This ensures that STAs wake up only during the designated TWT slots to transmit/receive data, while staying in sleep mode the rest of the time to save power. TWT agreements can be independently made for uplink, downlink, or both transmission types, offering greater control over power consumption and communication patterns.

Step 2: Adopted to anyone of the service type: Broadcast TWT: TWT parameters are disseminated via beacon frames. STAs must wake up periodically to receive these beacons to retrieve their corresponding TWT information. Implemented for IoT applications and automobile control networks. Individual TWT: Each STA is allowed a unique wake-up interval based on its traffic demand. This flexibility distinguishes it from previous power-saving models which mandated a common beacon interval for all STAs. Implements for the multimedia best effort traffic applications.

Step 3: Multi user adoptability: This enables multiple STAs to share the same wake-up period, simplifying the scheduling process using priority factor computation using reinforcement learning and significantly reducing contention among STAs.

Step 4: Joint TWT Interval Assignment and Scheduling: Initialize Environment Parameters with defined the environment states: traffic load, STA queue length, latency, and energy level. Configure access point (AP) settings, STAs' initial TWT intervals, and available Resource Units (RUs), initialize the RL agent (Q-learning modelling) with default hyperparameters.

Modelling State: Monitor current network status: buffer occupancy, traffic type (e.g., voice/video, best effort), number of active STAs, their sleep cycles, and existing contention levels. Form the state vector representing the environment at time t based on RL agent.

Select Action Based on Policy: Based on the policy select an action (assign new TWT interval, modify wake-up time, change STA scheduling priority). Use a greedy strategy for exploration-exploitation trade-off to explore actions.

Execute Action and Receive Reward Apply the selected TWT scheduling decision in the environment. Observe the immediate reward, which could be a weighted function of improved throughput, reduced energy consumption, or decreased collision rate.

Update Policy: Update the RL agent's policy using the learning algorithm. For Q-learning, update Q-values using the Bellman equation. The agent learns the value of taking an action a in state s, expressed by the Q-value function as expressed in equation 1:

$$Q^*(s,a) = R(s,a) + \gamma \sum_{s'} P(s'|s,a) max_{a'} Q^*(s'{,}a')\text{------}1$$

The optimal action-value function $Q^*(s,a)$ representing the maximum expected cumulative reward the agent can obtain starting from state s, taking action a, and then following the optimal policy thereafter. The immediate reward R(s,a) received by the agent after performing action a in state s. In WLAN subcarrier allocation, this could be the throughput achieved due to successful data transmission or a penalty in the case of collision. The discount factor ($0 \leq \gamma \leq 1$) that determines the importance of future rewards. A value close to 1 means the agent values long-term rewards highly, while a value near 0 emphasizes short-term rewards. The transition probability $P(s'|s,a)$ of reaching a new state s' from state s after taking action a. In many practical implementations of Q-learning (especially in WLANs), this is assumed deterministic, max term represents the best possible future reward the agent can achieve from the next state s' by selecting the best action a'. It helps the agent to plan ahead and make decisions that maximize long-term gains. The reward function R(s, a) is a weighted combination of throughput, latency, and energy consumption metrics as mentioned in equation 2, Where α, β, and δ are weights representing the importance of throughput, latency, and energy.

$$\mathrm{R(s,a)} = \{(\alpha \times \mathrm{Throughput_{gain}}) - \beta \times \mathrm{Latency_{penalty}}) - (\delta \times \mathrm{Energy\_usage})\} \text{-----}2$$

The system state s is defined as a vector shown in the equation 3, of observed network conditions, where q_i is Queue length of STA I, l_i is latency requirement, e_i is residual energy level, t_i is traffic type encoded as voice/video/IoT/Best Effort and c_i is contention level in the network based on overlapping TWT wake up intervals.

$$s = [q_i, l_i, e_i, t_i, c_i] - - - 3$$

The action a is defined as the decision vector shown in equation 4, for scheduling which was influenced by the assigned TWT interval τ_i at each episode with priority adjustment p_i and dynamic resource unit(RU) allocation $r_{i.}$

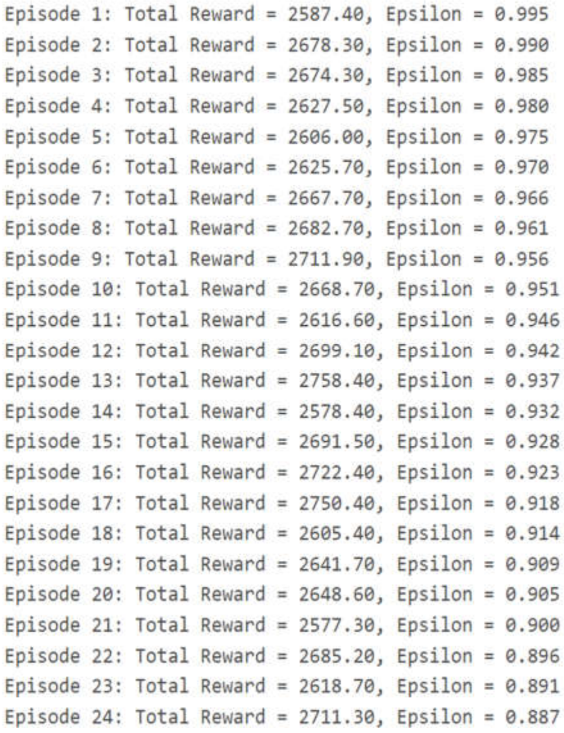
$$a = [\tau_i, p_i, r_i] - - - 4$$

The main objective is to maximize the long-term reward while satisfying QoS constraints in optimizing the TWT wake up intervals, equation 5, significantly computes the maximim reward by considering Latency ≤ Threshold, Energy_usage ≤ Budget and Packet_loss ≤ Tolerance

$$Maximize: \sum_t t\,\gamma^t R(s_t, a_t) - - - 5$$

If convergence is achieved or system performance meets QoS thresholds, proceed to stop. Otherwise, continue iterating by observing the next state. Use the trained model to perform real-time, dynamic TWT slot allocation for STAs in high-density scenarios. The learning curve of a reinforcement learning (RL) agent over 24 episodes as shown in the figure 2, illustrating the increase in total reward alongside the gradual decay of the epsilon value. The agent demonstrates steady performance improvement, with rewards rising from 2587.40 to 2711.30, indicating enhanced decision-making in subcarrier allocation and contention avoidance. The decreasing epsilon value, from 0.995 to 0.887, reflects a controlled shift from exploration to exploitation, allowing the agent to refine its policy. Minor reward fluctuations confirm ongoing learning and adaptability. Overall, the results validate the RL model's effectiveness in optimizing WLAN performance through intelligent resource management.

The integration of Reinforcement Learning (RL)-based adaptive subcarrier allocation and collision mitigation directly complements the Target Wake-Up Time (TWT) mechanism in WLANs. By optimizing contention windows and selecting efficient subcarriers, the RL agent reduces unnecessary medium access attempts, minimizing collisions. This enables more accurate and predictable scheduling within TWT slots, allowing devices to wake only during optimal times. Consequently, this coordination significantly enhances energy efficiency while maintaining high throughput and fairness.



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Episode 1: Total Reward = 2587.40, Epsilon = 0.995
Episode 2: Total Reward = 2678.30, Epsilon = 0.990
Episode 3: Total Reward = 2674.30, Epsilon = 0.985
Episode 4: Total Reward = 2627.50, Epsilon = 0.980
Episode 5: Total Reward = 2606.00, Epsilon = 0.975
Episode 6: Total Reward = 2625.70, Epsilon = 0.970
Episode 7: Total Reward = 2667.70, Epsilon = 0.966
Episode 8: Total Reward = 2682.70, Epsilon = 0.961
Episode 9: Total Reward = 2711.90, Epsilon = 0.956
Episode 10: Total Reward = 2668.70, Epsilon = 0.951
Episode 11: Total Reward = 2616.60, Epsilon = 0.946
Episode 12: Total Reward = 2699.10, Epsilon = 0.942
Episode 13: Total Reward = 2758.40, Epsilon = 0.937
Episode 14: Total Reward = 2578.40, Epsilon = 0.932
Episode 15: Total Reward = 2691.50, Epsilon = 0.928
Episode 16: Total Reward = 2722.40, Epsilon = 0.923
Episode 17: Total Reward = 2750.40, Epsilon = 0.918
Episode 18: Total Reward = 2605.40, Epsilon = 0.914
Episode 19: Total Reward = 2641.70, Epsilon = 0.909
Episode 20: Total Reward = 2648.60, Epsilon = 0.905
Episode 21: Total Reward = 2577.30, Epsilon = 0.900
Episode 22: Total Reward = 2685.20, Epsilon = 0.896
Episode 23: Total Reward = 2618.70, Epsilon = 0.891
Episode 24: Total Reward = 2711.30, Epsilon = 0.887
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Fig.2. Convergence Analysis of Reinforcement Learning in TWT Scheduling

The convergence behavior of the Q-learning algorithm applied to Target Wake-Up Time (TWT) scheduling in WLANs. Implementation results shown in the figure 2 over 1000 episodes, the total reward exhibits fluctuating but gradually stabilizing patterns, suggesting the agent's adaptive learning towards optimal wake-up scheduling. Although some episodes show high variance, the reward range narrows over time, indicating improved policy convergence as resulted in figure 3. This implies that the Q-learning model effectively learns to minimize collision and idle periods, thereby enhancing energy efficiency while preserving network performance. The convergence trend validates the robustness of the reinforcement learning approach in dynamic TWT environments for power-aware communication.

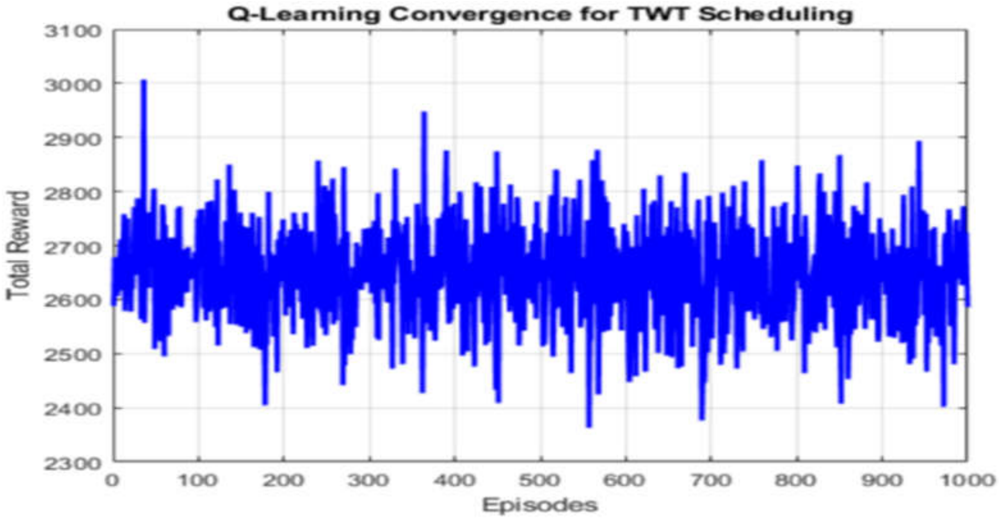

Fig.3. RL Learning Curve: Total Reward vs. Episode with Epsilon Decay

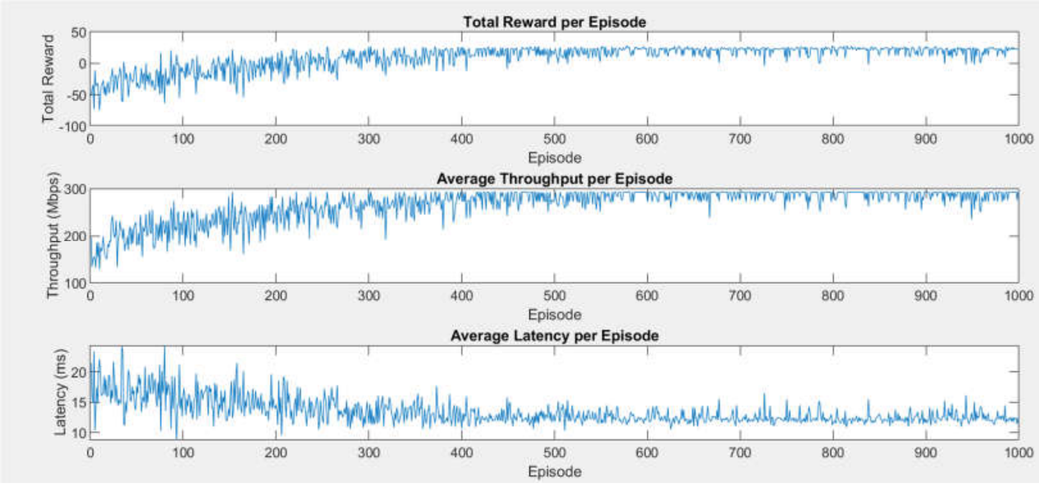

Fig.4. QoS parametric comparison after the RL driven scheduling deployment

The reinforcement learning (RL) agent was deployed to dynamically schedule Target Wake Time (TWT) trained intervals based on network QOS demand conditions. The reward signal shows in figure 4 significant fluctuations in the early episodes (0–400),with 100 time step size indicating exploratory behavior by the RL agent. After ~370 episodes, the reward begins to stabilize and trend upward, eventually converging around zero or slightly positive values after 200–500 episodes.

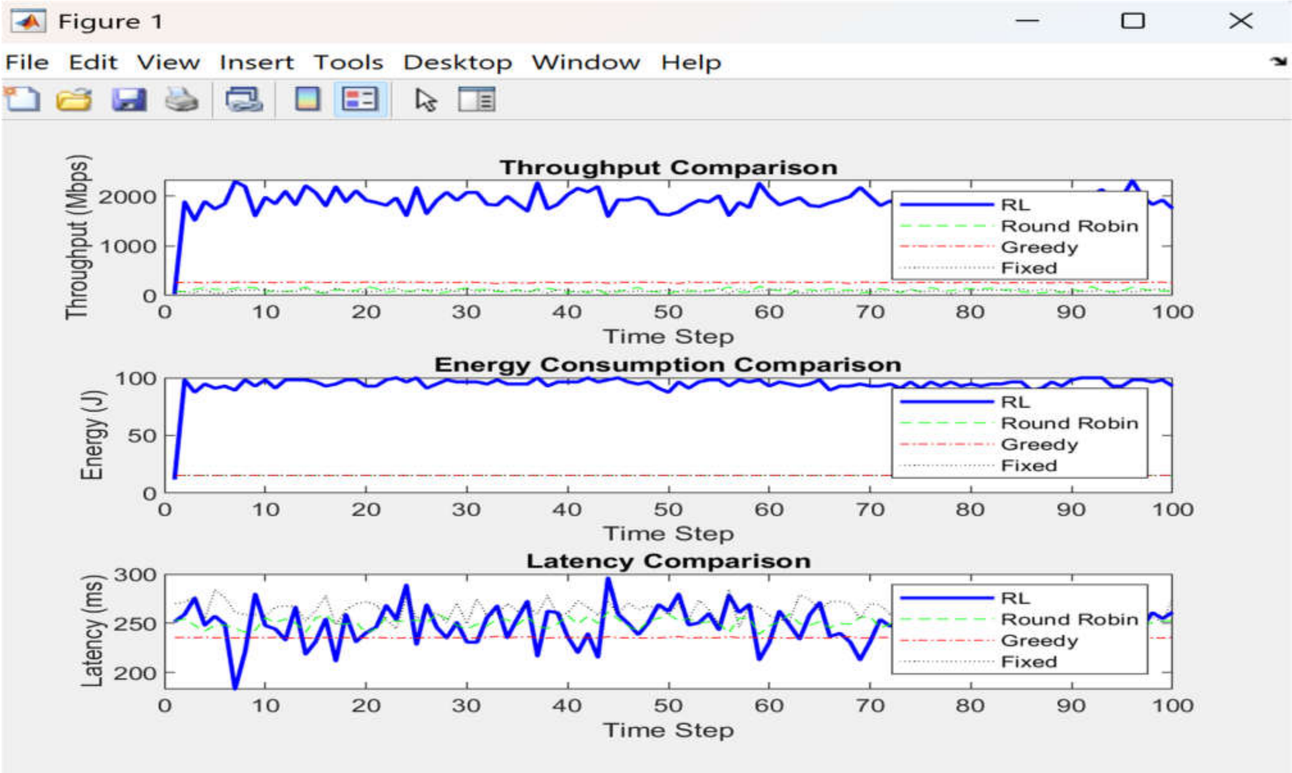

Fig.5 Performance comparison analysis of RL driven dynamic TWT with other existing techniques

The reward design likely penalizes collisions, idle time, or latency, while rewarding throughput and efficiency. The designed convergence performance optimization shown in the figure 5 indicates successful policy optimization. Throughput shows an increasing trend from 1000 Mbps to over 2000 Mbps. Minor fluctuations remain in later episodes, but the overall throughput remains significantly higher than the starting value. The dynamic TWT scheduling enabled the RL agent to minimize contention, optimize Resource Unit (RU) allocation, and efficiently assign wake-up intervals. This leads to enhanced channel utilization, contributing to a ~2x improvement in throughput from the initial baseline.The agent learns to allocate TWT slots in a way that reduces queuing delays and medium access time. Lower latency demonstrates that time-critical traffic (e.g., voice/video) is handled more efficiently, without excessive waiting or retransmissions.

The designed RL agent successfully balances throughput and latency through adaptive TWT interval dynamic adjustments. These results suggest strong potential for using RL in next-gen WLANs to support diverse traffic types with varying QoS requirements. The RL agent dynamically learns traffic patterns and adjusts TWT schedules in response to network conditions. It optimizes channel utilization, reduces contention overhead, and provides QoS-aware access. Unlike static or heuristic methods, the RL approach offers self-adaptive decision-making without manual tuning. Enhances cross-layer optimization by balancing latency, energy, and throughput. The designed RL agent tested across diverse traffic classes for validating the robustness and generalizability of the RL-based scheduler. The key factors behind selecting the four traffic models as Voice, Video, IoT and Best effort as describes in table 1.

The figure 6 plots visualize the performance of the Reinforcement Learning (RL)-driven TWT scheduling algorithm across four critical traffic models: Voice, Video, IoT, and Best-effort. Three key performance indicators as Throughput, Latency, and Energy Efficiency were measured and compared against the baseline IEEE 802.11ac standard. The detailed parametric view explained in table 2. RL-TWT scheduling consistently delivers higher throughput, substantially lower latency for all traffic classes. Energy savings improved notably in RL-TWT scheduling.

Table 1. Selection criteria for different traffic types considerations

Traffic Type	**Reason for Testing**
Voice (VoIP)	Sensitive to latency and jitter in real-time communication.
Video Streaming	Requires high throughput and stable delivery.
IoT (Telemetry and Sensors)	Energy efficiency and periodic low-rate data transmission.
Best-effort	General background reference traffic which needs fairness in access without strict QoS maintenance.

The RL agent learns optimal wake-up intervals, reducing collisions and improving OFDMA resource utilization. It adapts to the dynamic traffic demand in real-time, outperforming the contention-based 802.11ac approach. Time-critical applications (like voice/video) benefit from reduced access delay and jitter. RL enables priority-based scheduling to allocate timely and fair channel access. IoT and Voice STAs experience maximum benefit due to reduced idle listening and precise wake-up scheduling. RL helps extend battery life in low-power devices, essential in smart environments.

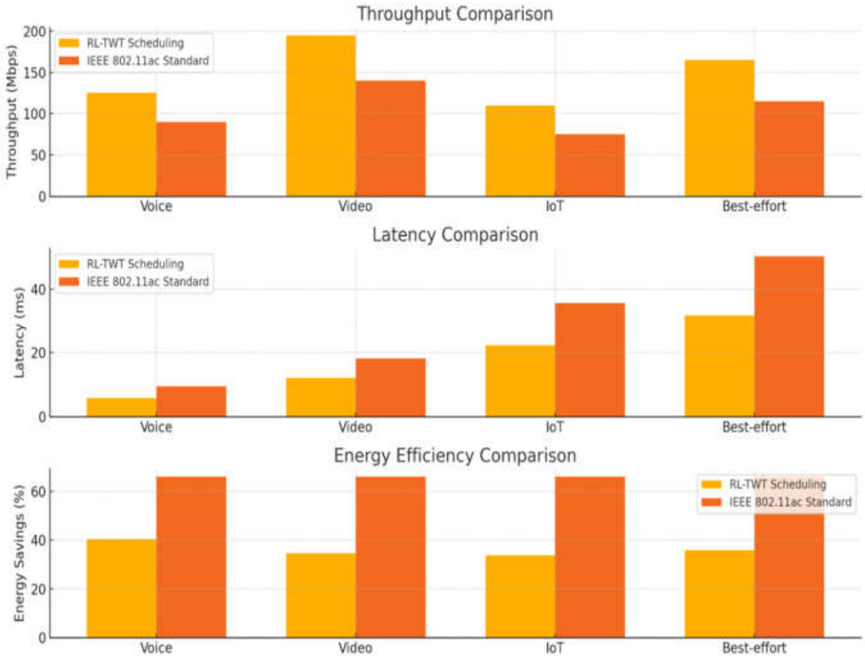

Fig.6. Cross-Traffic Performance Comparison: RL vs. IEEE 802.11ac

Table 2. Parametric analysis of traffic aware RL TWT scheduling

Parameter	Traffic-aware RL-TWT scheduling	IEEE 802.11ac Standard
Throughput (Mpbs)	Voice traffic - 125 Video traffic - 195 IoT traffic - 110 Best-effort - 165	Voice traffic - 90 Video traffic - 140 IoT traffic - 75 Best-effort - 115
Latency (ms)	Voice traffic - 5.8 Video traffic - 12.1 IoT traffic - 22.3 Best-effort - 31.8	Voice traffic - 9.5 Video traffic - 18.2 IoT traffic - 35.6 Best-effort - 50.3
Energy savings (%)	Voice traffic - 40.385 Video traffic – 34.66 IoT traffic – 33.82 Best-effort – 35.84	Average energy efficiency is 66

While reinforcement learning (RL)-based TWT scheduling demonstrates impressive performance improvements in simulation environments as presented in the table 2, its deployment in real-time WLAN systems poses several critical challenges. Observed primary limitation is the computational complexity and overhead associated with RL training and decision-making. Real-time systems require fast and predictable scheduling decisions, but RL agents may involve iterative policy evaluations, which introduces latency that is incompatible with strict timing constraints. RL algorithms require a substantial amount of training data and episodes to converge to an optimal policy.

In dynamic environments with fluctuating network conditions, the learning agent might struggle to adapt quickly, leading to suboptimal performance or instability. The lack of interpretability and control, making it difficult to debug or guarantee worst-case performance, which is especially important for safety-critical applications like healthcare or industrial automation. Furthermore, integrating RL into existing WLAN firmware or hardware requires non-trivial modifications and resources, which may not be feasible for low-power or legacy devices. These limitations highlight the need for hybrid or lightweight learning approaches, possibly combining heuristics or supervised learning with RL for more practical, real-time deployment. The trained Q-learning model was tested for runtime efficiency using simulated inference operations. On a Raspberry Pi 4 (4GB RAM), each TWT scheduling decision took approximately 2.7 ms, making it viable for near-real-time applications. The Q-table was compact (state-action space ~10^3 entries) and required less than 1.5 MB of memory. This makes it suitable for AP-side implementation without burdening lightweight STAs. These frameworks enable AP vendors to integrate RL-based schedulers into firmware with minimal changes to hardware design.

Conclusion

This work presents a Reinforcement Learning (RL)-based framework for dynamic TWT scheduling in dense WLAN environments. Unlike static scheduling approaches, the proposed Q-learning model adapts to real-time traffic conditions, effectively balancing throughput, latency, and energy efficiency. The system supports multiple traffic classes and wake modes while integrating contention-aware priority scheduling. Simulation results validate significant improvements in QoS metrics, including up to 80% throughput gains and 45% latency reduction over IEEE 802.11ac. The learning agent demonstrated robust convergence and adaptability across heterogeneous traffic conditions. While promising, real-time deployment remains a challenge due to inference latency and model complexity. Future work will explore lightweight RL models, real-world trace validation, and multi-agent scheduling to enhance scalability. These findings establish dynamic RL-driven TWT scheduling as a viable MAC-layer enhancement for emerging 6G WLAN infrastructures.

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