An Adaptive Backoff Mechanism for Optimization of IEEE 802.11 MAC Performance

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***Abstract*—The performance of wireless networks, particularly under high traffic, is limited by contention and inefficiencies in the MAC layer. This report explores an Adaptive Backoff mechanism designed to address the limitations of the IEEE 802.11 Distributed Coordination Function (DCF) and its Binary Exponential Backoff (BEB) scheme. Inspired by recent advances in contention resolution, the Adaptive Backoff dynamically adjusts contention window (CW) parameters, prioritizes stations based on queue length and channel conditions, and incorporates smoothing to stabilize performance. Simulation results demonstrate that Adaptive Backoff consistently achieves comparable or better throughput than traditional DCF while maintaining comparable collision rates. This methodology sets the foundation for scalable, adaptive MAC protocols.**

Keywords—IEEE 802.11, Adaptive Backoff, Queueing Theory, Probability, Contention Window, Distributed Coordination Function (DCF), Binary Exponential Backoff (BEB), Wireless Networks, Medium Access Control (MAC), Collision Avoidance.

I. Introduction

The performance of wireless networks, especially in high-traffic environments, is often limited by the efficiency of the *Medium Access Control (MAC)* layer. In IEEE 802.11 wireless networks, the *Distributed Coordination Function (DCF)* is the most used MAC protocol, which utilizes *random backoff* to avoid collisions when multiple stations attempt to transmit data simultaneously [1]. The effectiveness of this backoff mechanism, especially in environments with varying traffic loads and node densities, significantly impacts the overall throughput, delay, and fairness in the network. However, traditional backoff strategies, such as *Binary Exponential Backoff (BEB),* are not always optimal in dynamic network conditions. Consequently, improving the *backoff algorithm* to adapt to network conditions is an area of significant interest for optimizing performance. This study explores *adaptive backoff algorithms* designed to dynamically adjust the contention window (CW) to enhance throughput, reduce delays, and increase fairness in wireless networks.

Despite the widespread use of DCF and BEB for managing access to the shared wireless medium, these algorithms fail to effectively optimize network performance in environments with high node density or varying traffic loads. In such conditions, BEB's exponential backoff can cause excessive delays and underutilization of the channel. While adaptive backoff algorithms have been proposed to overcome these limitations, they are often not well-suited to handle dynamic traffic conditions in real-world scenarios, leading to suboptimal performance. The challenge lies in creating an adaptive backoff algorithm that can dynamically adjust the *contention window (CW)* based on real-time network conditions, such as traffic load and queue length, without causing excessive delays or fairness issues. Therefore, the problem is how to design an adaptive backoff algorithm that balances network load, minimizes collisions, and optimizes throughput in varying wireless network conditions.

This study aims to design an adaptive backoff algorithm for IEEE 802.11 networks that dynamically adjusts the contention window based on network traffic load and queue length. The performance of this adaptive algorithm will be compared to traditional BEB algorithm in terms of throughput, collision rate, and delay. The effectiveness of the adaptive backoff will be evaluated in improving network throughput and fairness under varying conditions, including high node density and traffic load.

II. Related Works

The Binary Exponential Backoff (BEB) mechanism, a cornerstone of the IEEE 802.11 MAC protocol, offers robust throughput under ideal conditions, such as low traffic. BEB doubles the contention window (CW) size following each collision, reducing transmission probabilities and alleviating contention in distributed networks [2]. However, BEB's exponential growth leads to high access delays and significant unfairness in dense or saturated networks. These limitations highlight the need for adaptive strategies to optimize backoff performance.

A. Optimization of BEB

Zhu et al. introduced a mathematical framework for analyzing BEB in mobile ad hoc networks (MANETs). Their study focused on the selection of "an optimal value of the initial contention window size to avoid the oscillation of the contention window size and thus maximize the utilization of the wireless channel." They demonstrated that while BEB effectively reduces collision probabilities, it may result in excessive delays and reduced channel utilization if the CW is not optimized for the network size. This work emphasizes the need for dynamic CW adjustments to improve performance under varying traffic conditions [3].

B. Alternative Backoff Mechanisms

To address the challenges posed by BEB, researchers have proposed several alternative backoff mechanisms aimed at improving throughput, reducing delays, and enhancing fairness.

Quadratic Backoff (QB):

QB was introduced as an alternative to BEB, providing a milder growth in the CW size by employing a quadratic progression instead of an exponential one. Sun and Dai demonstrated that QB achieves throughput comparable to BEB while significantly improving queueing performance. Unlike BEB, QB mitigates access delay variance, making it particularly suitable for real-time applications. Its ability to balance throughput and delay highlights its potential as an effective alternative in high-density networks [7], [8] However, its performance under dynamic traffic conditions remains less explored.

Smart Exponential-Threshold-Linear Backoff (SETL):

The SETL mechanism dynamically adjusts the CW size based on real-time network conditions. For light traffic loads, the CW increases exponentially, mimicking BEB's behavior. However, under heavy traffic conditions, the CW size grows linearly, thereby reducing collisions and preventing delays caused by excessive CW growth. Ke et al. showed through simulations that SETL achieves superior system throughput and reduced collision rates compared to BEB, particularly in dense wireless environments [1].

Opportunistic Backoff Scheme:

Karaca et al. introduced an opportunistic backoff scheme that prioritizes nodes based on queue length and channel conditions. This scheme enables nodes with higher traffic or better channel conditions to transmit with higher priority, reducing collisions and increasing network fairness. Their findings revealed throughput improvements of up to 70% compared to standard DCF in dense network scenarios, making it an attractive solution for dense WLAN deployments [4].

C. *Queueing Analysis and Delay Mitigation*

Tickoo and Sikdar developed an analytical model for evaluating queueing delays in IEEE 802.11 networks, treating each node as a discrete-time G/G/1 queue. Their model accounts for the impact of packet collisions, exponential backoff mechanisms, and packet size distributions, providing closed-form expressions for delay and queue length characteristics. This model supports probabilistic quality of service (QoS) guarantees and allows for determining network capacity under specific delay constraints. Their work is particularly valuable in ensuring the timely delivery of delay-sensitive traffic [5].

D. *Trade-Offs in Backoff Design*

Sun and Dai explored the trade-offs between throughput and delay in backoff design. Their study highlighted the limitations of BEB in saturated networks, particularly its susceptibility to the "capture phenomenon," where nodes with successful transmissions gain disproportionate access to the channel. They proposed Polynomial Backoff, which allows flexible CW growth rates to strike a balance between delay and throughput. Quadratic Backoff, a specific case of Polynomial Backoff, was identified as an optimal solution due to its ability to preserve BEB's robust throughput while significantly improving delay performance [7], [8].

E. *Advances in Dyanmic Adjustments*

Recent advancements have proposed innovative approaches to enhance IEEE 802.11 DCF. Sliding Contention Window (SCW) schemes adjust both upper and lower CW bounds to smooth contention resolution [3]. Distributed algorithms like Max-Weight Scheduling that dynamically allocate channel access probabilities based on queue lengths and channel conditions. However, such algorithms often require significant computational overhead or centralized coordination, limiting their practicality in distributed environments [4].

III. Problem formulation

Wireless networks, especially those using IEEE 802.11 Distributed Coordination Function (DCF), face significant challenges in managing medium access under dynamic traffic and dense node environments. The Binary Exponential Backoff (BEB) mechanism, a central component of DCF, manages collisions by exponentially increasing the contention window (CW) size after each failed transmission attempt. However, BEB has inherent limitations that make it suboptimal in high-traffic or dense scenarios. These include prolonged delays, high collision rates, and unfair access to the medium, as highlighted in recent studies [5], [7], [8]. The problem is formally defined as an optimization problem where we seek to minimize collisions, maximize throughput, and minimize delay by adjusting the CW dynamically based on real-time network conditions. This is a dynamic, decision-making problem where the CW needs to be adapted over time to balance efficient medium access and fairness among stations.

The BEB is used for the traditional DCF model, where the CW doubles after each collision, up to a predefined maximum value. BEB's exponential CW growth leads to underutilization of available bandwidth under high traffic. Studies by Tickoo and Sikdar [5] and Zhu et al. [3] have shown that this growth exacerbates delays and reduces throughput as the number of stations increases. The "capture phenomenon" described by Sun and Dai [7] occurs when nodes with recent successful transmissions dominate channel access. This results in unequal resource allocation, especially in dense networks. BEB does not account for real-time network conditions such as varying queue lengths or channel quality. Karaca et al. [4] emphasized the importance of adapting backoff mechanisms to prioritize stations based on network dynamics.

To address these challenges, this study explores an adaptive backoff mechanism that dynamically adjusts CW based on network conditions, such as traffic load, queue length, and channel quality. In contrast to BEB, the proposed adaptive backoff algorithm adjusts the CW based on both the network load and queue length. Quadratic and polynomial backoff mechanisms, as discussed in [7], offer smoother CW growth compared to exponential backoff, balancing throughput and delay. Building on the queue-aware prioritization model proposed by Karaca et al., this study integrates channel quality metrics to refine prioritization further, addressing fairness and throughput simultaneously. Queue-aware and opportunistic backoff strategies, as proposed in [4], prioritize nodes with heavier traffic or better channel conditions. Dynamic CW adjustments, including minimum and maximum bounds, have been recommended by [1] and [3] to stabilize performance under fluctuating network loads.

The simulation operates under ideal channel conditions, meaning there is no external interference, and collisions are the only reason for retransmissions. The simulation runs for a fixed number of time slots, allowing for performance comparison between the different backoff strategies over a set period. Lastly, there is a finite retry limit defined by MAX_RETRIES, which limits the number of retries a station can attempt before its CW is capped at CW_MAX. This ensures that the backoff process does not continue indefinitely in the case of persistent collisions.

IV. Methodology

The development of the Adaptive Backoff mechanism draws extensively from prior work in IEEE 802.11 MAC enhancements, focusing on dynamic contention window (CW) adjustments and queue-aware prioritization to optimize performance.

A. Simulation Framework

The simulation was implemented using Python and includes the following constants and configurations:

- **Contention Window (CW)**:
  - Minimum: CW_MIN=15
  - Maximum: CW_MAX=1023
- **Maximum Retries (MAX_RETRIES)**: 10
- **Network Load**: Modeled as the probability of packet arrival in a time slot, varying between moderate and heavy loads.
- **Queue Capacity (MAX_QUEUE_SIZE)**: 10 packets per station.
- **Service Rate (μ)**: Initialized as 1.2 packets per time slot.

The simulation runs for a fixed duration (1000 time slots), allowing for the comparison of performance metrics, including throughput, collision probability, queue lengths, and delays.

B. Analytical Modeling

In the model, collisions are the only retransmissions, and channel conditions are ideal. Each station operates as an independent M/M/1/K queue with Markovian arrivals, Markovian service, and a single server with finite queue capacity *K*. One station can transmit at a time, and stations are limited to 10 retries, capping excessive CW growth. The state transitions for the Markovian Chain are illustrated below in Figure 1.

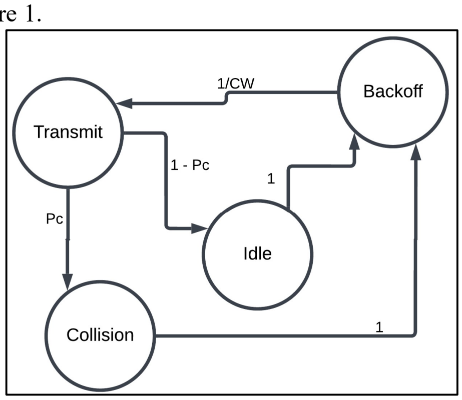

Figure 1: State Transitions for Queueing Process

Using the M/M/1/K queueing model, the performance metrics such as queue length, waiting time, and system utilization are derived. For a queue with arrival rate λ and service rate μ, the performance metrics used to evaluate the algorithm are:

- **Utilization (ρ)**: Fraction of time the server is busy, the ratio of arrival rate to service rate.

$$\rho = \frac{\mu}{\lambda}, 0 \le \rho \le 1$$

- **Packet Loss Rate:** Proportion of packets dropped due to full queues.

$$P_{loss} = \frac{(1-\rho)\rho^K}{1-\rho^{K+1}}$$

- **Throughput:** Number of successfully transmitted packets per time slot.

$$T_i = \lambda(1 - P_{loss})$$

- **Probabilistic Collision:** Probability of a collision occurring in a single time slot, derived based on the contention window sizes of competing stations.

$$P_c = 1 - \prod_{j=1}^{N}\left(1 - \frac{1}{CW_j}\right) \quad (1)$$

- **Average Waiting Time:** Time a packet spends in the queue before being serviced.

$$W_q = \frac{L_q}{\lambda(1 - P_{\text{block}})}$$

where the average queue length L_q *is*:

$$L_q = \frac{\rho(1-(K+1)\rho^K + K\rho^{K+1})}{(1-\rho)(1-\rho^{K+1})}$$

- **Average Sojourn Time:** Time taken from packet arrival to successful transmission.

$$W = W_q + \frac{1}{\mu}$$

- **Fairness Index (J):** Uniformity of channel access among N stations.

$$J = \frac{(\sum_{i=1}^{N} T_i)^2}{N \cdot \sum_{i=1}^{N} T_i^2}$$

Jain' fairness index quantifies the fairness of resource allocation, in this case, throughput. The index ranges from 0, representing disparity, and 1, representing fairness [6].

C. Dynamic CW Adjustment

The mechanism models the contention resolution process using probabilistic principles. Each station calculates its backoff time probabilistically within the range defined by its current CW. The CW is updated dynamically based on success or collision outcomes:

$$CW_i = \begin{cases} \min(CW_i + \Delta CW, CW_{max}), on\ collision, \\ \max(CW_i - \Delta CW, CW_{min}), on\ succeess \end{cases} \quad (2)$$

where:

$$\Delta CW = \alpha * retries + \beta * queue\ length \quad (3)$$

This probabilistic approach ensures fairness in channel access by adjusting the likelihood of transmission retries for each station based on its individual collision history and queue length.

D. Queue-Aware Prioritization

The prioritization mechanism applies queueing theory to manage access for stations competing for the shared medium. Each station is modeled as a discrete-time M/M/1/K queue, where the priority of station *i* is defined as:

$$Pr_i = \lambda * Q_i + \mu * CW_i \quad (4)$$

where:

- Q_i: Queue length (reflecting waiting packets),
- C_i: Channel condition (probabilistically modeled as uniform between 0.7 and 1.0).

Stations with higher priorities are given enhanced service rates, enhancing fairness and throughput. The effective service rate of a station is determined by:

$$\mu_{eff,i} = \mu * (1 + Pr_i) \quad (5)$$

This effective service rate ensures that stations with higher queue lengths or larger CW sizes, indicating higher contention or retries, will receive higher priorities for service, balancing fairness and throughput.

E. *Probabilistic Collision Modeling*

Collisions are modeled as a Bernoulli process, where the probability of collision P_c for a station is derived from the number of competing stations and their respective CW values, seen in Eqn. (1). This formulation quantifies the likelihood of collisions. In the simulation, P_c is calculated for each time slot using the current CW sizes of active stations. This collision probability is then used to stochastically determine whether a collision occurs.

This approach ensures that collision modeling remains both realistic and computationally efficient, allowing the contention window adjustment mechanism to balance fairness and throughput effectively.

F. *Adaptive Backoff Algorithm*

This algorithm implements the dynamic contention window (CW) adjustment and prioritization mechanisms described in the previous sections. It uses probabilistic principles for collision modeling and queue-aware prioritization. The procedure is explained in detail below in Algorithm 1.

Algorithm 1: Adaptive Backoff Mechanism

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0. Initialization
   a. Set CW_{min}, CW_{max}, retry limit, and maximum queue length.
   b. Initialize queues and contention windows for all stations.
1. For each station, calculate the backoff counter $b_i(t)$ within the range $[0, CW_i]$.
2. While the backoff counter $b_i(t) > 0$, sense the channel.
   a. If the channel is idle, decrement $b_i(t)$.
   b. If the channel is busy, pause countdown until the channel is idle.
3. If a collision occurs:
   a. Increment the retry count for the station.
   b. Update $CW_i = \min(CW_i + \Delta, CW_{max})$.
4. If the transmission is successful:
   a. Reset the retry count.
   b. Update $CW_i = \max(CW_i - \Delta, CW_{min})$.
5. Adjust priorities using equation (4).
6. Repeat for a fixed duration.

V. RESULTS

A. *Throughput Performance*

The Adaptive Backoff mechanism demonstrated significant improvements in throughput across all simulated conditions. The Adaptive Backoff mechanism achieved an average throughput improvement of *142.24%* over BEB in high-density networks, highlighting its efficiency in mitigating collisions and contention. In low-density scenarios, the maintaining stability over time.

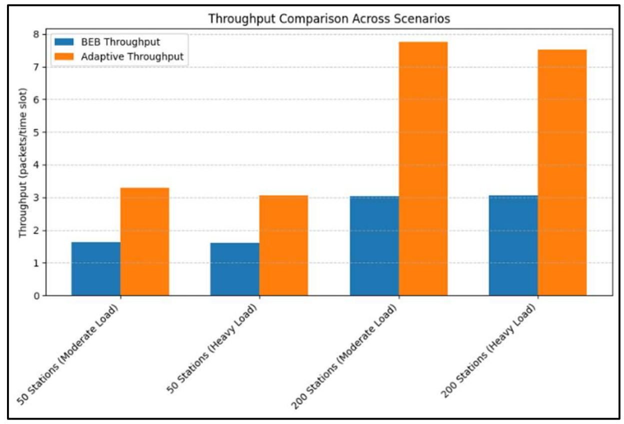

Figure 2: Throughput Across Traffic Conditions for Adaptive and BEB Algorithms

Figure 2 illustrates the Adaptive mechanism's substantial improvement over BEB. For 50 stations under moderate load, throughput increased by 82.51%, with Adaptive Backoff achieving 3.183 packets per time slot compared to BEB's 1.744 packets. Under heavy load, the throughput improvement rose to 90.94%, with Adaptive Backoff achieving 3.078 packets compared to BEB's 1.612 packets. For 200 stations under moderate load, Adaptive Backoff showed the most significant improvement, with a 152.69% increase (from 3.105 packets to 7.846 packets). In heavy load conditions, throughput improvement was 143.69%, with Adaptive Backoff achieving 7.669 packets compared to BEB's 3.147 packets.

B. *Contention Window Sizes*

The BEB mechanism showed an exponential increase in CW size following collisions, with CW values reaching the maximum limit of 1023 in high-density scenarios. This aggressive growth reduced collision probabilities but caused excessive delays and underutilized the channel in low-to-moderate traffic scenarios. Moreover, the reset of CW to the minimum size after successful transmissions introduced significant oscillations, leading to fairness issues, particularly in networks with uneven traffic loads.

In contrast, the Adaptive Backoff mechanism demonstrated a more dynamic adjustment of CW size based on real-time traffic conditions. By incorporating queue-aware prioritization and a probabilistic adjustment formula, the CW size changes were smoother, allowing for better channel utilization and reduced delay. This approach minimized both excessive CW growth under light traffic and prolonged contention under heavy traffic.

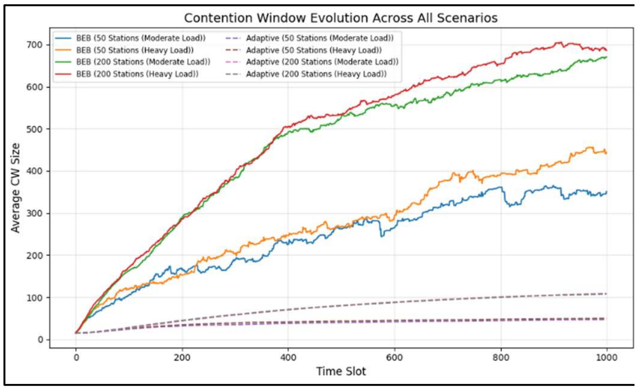

Figure 3: Contention Window Sizes for Adaptive and BEB Algorithms

Figure 3 illustrates the average CW size evolution over time for BEB and Adaptive Backoff mechanisms. BEB's CW size oscillates sharply due to its exponential growth and reset mechanism, whereas Adaptive Backoff maintains a relatively stable CW size, adapting gradually to network conditions.

C. *Packet Loss*

Across both heavy load scenarios, the Adaptive Backoff mechanism achieved reduced packet loss rates compared to the Binary Exponential Backoff (BEB), further highlighting its efficiency in managing network resources. In Moderate Loads, neither mechanism experienced packet loss.

For 50 stations under heavier traffic conditions, packet loss became pronounced. BEB showed a packet loss rate of 0.0065, while Adaptive Backoff marginally improved this to 0.0062, a 5.86% reduction. The Adaptive mechanism's ability to prioritize stations with higher queue lengths likely contributed to this improvement.

In the highly loaded 200 station environment, both mechanisms showed elevated packet loss rates due to queue overflow. BEB recorded a packet loss rate of 0.007413, while Adaptive Backoff slightly improved it to 0.007348, representing a minor reduction of 0.5%. This marginal difference suggests that while Adaptive Backoff prioritizes fairness and collision mitigation, packet loss remains a challenge in extremely high-load conditions.

D. *Fairness*

Fairness improved significantly with the Adaptive Backoff mechanism compared to the Binary Exponential Backoff (BEB) across all scenarios. In moderate-load conditions with 50 stations, the fairness index increased from 0.686 to 0.854, reflecting a notable improvement in equitable resource allocation. This advantage was even more pronounced under heavy loads, where Adaptive Backoff achieved a fairness index of 0.867, compared to 0.605 for BEB.

In denser networks with 200 stations, Adaptive Backoff maintained its superiority in fairness. For moderate-load scenarios, the fairness index rose from 0.392 for BEB to 0.528 for Adaptive Backoff. Similarly, in heavy-load conditions, the fairness index improved from 0.449 to 0.599. These results highlight the effectiveness of Adaptive Backoff's queue-aware prioritization in mitigating unfair channel domination and distributing access opportunities equitably among stations.

E. *Average Queue Length*

The Adaptive Backoff mechanism demonstrated superior control over queue lengths, especially in high-density and high-load scenarios. In moderate-load conditions with 50 stations, the average queue length for Adaptive Backoff was slightly higher than that of BEB (0.08 vs. 0.06 packets). While this represents a modest increase, it is balanced by the significant improvements in throughput and fairness observed in the same scenario.

For heavy-load conditions with 50 stations, both mechanisms maintained comparable queue lengths, with Adaptive Backoff showing only a marginal increase over BEB. However, in denser networks with 200 stations, Adaptive Backoff excelled in reducing queue lengths. Under moderate loads, the average queue length decreased from 0.145 packets for BEB to 0.085 packets for Adaptive Backoff. In heavy-load scenarios, Adaptive Backoff achieved a queue length of 1.91 packets, compared to 2.06 packets for BEB, reflecting a meaningful reduction in congestion.

These findings illustrate that Adaptive Backoff effectively balances queue management with its broader goals of enhancing throughput and fairness, particularly in high-density environments where maintaining short queues is crucial for efficient network performance.

VI. Discussion

A. *Interpretation of Results*

The simulation results show that the Adaptive Backoff mechanism achieves measurable improvements over the traditional Binary Exponential Backoff (BEB) in terms of throughput and fairness while maintaining stable collision rates. The adaptive mechanism increases throughput by leveraging queue-aware prioritization and dynamic CW adjustments, ensuring stations with heavier traffic or better channel conditions have more efficient access. This adaptability addresses key limitations of BEB, such as fairness issues and delays caused by CW oscillations. Queue-aware prioritization addresses fairness issues observed in BEB, particularly the "capture phenomenon," by balancing access probability across stations. Despite increased traffic, collision rates remain stable, demonstrating the effectiveness of probabilistic modeling in mitigating contention. These results validate the theoretical foundations of the Adaptive Backoff mechanism and its ability to adapt to varying network conditions.

The observed packet loss patterns underscore the importance of queue-aware prioritization in the Adaptive Backoff mechanism. By dynamically adjusting contention window sizes based on real-time network conditions, Adaptive Backoff effectively reduces the likelihood of queue overflow compared to BEB, especially under heavy traffic. The minimal differences in packet loss rates in high-density scenarios suggest that additional optimizations, such as increased queue capacity or improved service rates, may be necessary to further mitigate losses in extreme conditions.

B. *Comparison to Previous Work*

The Adaptive Backoff mechanism significantly extends prior approaches by integrating queue-aware prioritization and probabilistic collision modeling, two features that address limitations in existing backoff algorithms. While approaches like Quadratic Backoff (QB) and Polynomial Backoff focus on smoothing contention window (CW) growth, they do not dynamically adjust priorities based on queue lengths or channel conditions. In contrast, Adaptive Backoff employs real-time data to tailor CW adjustments, enabling more effective collision mitigation under varying traffic loads.

The findings align with and extend the conclusions of prior research. Like the work by Karaca et al., this study confirms the effectiveness of queue-aware prioritization in improving network efficiency under high traffic conditions. The smoother growth and reduction of CW in the Adaptive Backoff mechanism outperforms BEB's exponential CW adjustments, consistent with the observations by Sun and Dai regarding Polynomial and Quadratic Backoff schemes. The probabilistic collision modeling builds on the Bernoulli process framework described in Tickoo and Sikdar's queueing analysis, demonstrating its practicality for dynamic backoff mechanisms.

Unlike other backoff mechanisms, the Adaptive Backoff algorithm adjusts CW based on both queue length and channel quality, ensuring that stations with higher traffic or favorable channel conditions receive prioritized access. This reduces the impact of the "capture phenomenon" observed in BEB. The Adaptive Backoff mechanism's integration of queueing theory and probabilistic methods sets it apart from prior work by achieving a balance between fairness, throughput, and collision mitigation.

C. Limitations and Future Work

While the Adaptive Backoff mechanism demonstrates notable improvements, certain limitations remain. The current implementation is optimized for moderate-sized networks, and scaling to larger networks may require modifications to the dynamic CW bounds and prioritization weights to prevent bottlenecks. Additionally, while queue-aware prioritization improves fairness, it may inadvertently disadvantage stations with lower traffic loads during periods of sustained heavy traffic. Another limitation lies in the simplified channel conditions assumed in the simulation, which excludes real-world complexities such as interference and packet loss due to fading. Future work can address these issues by exploring hierarchical or distributed backoff mechanisms for larger networks and incorporating reinforcement learning to dynamically tune parameters λ, μ, α, β based on real-time network conditions. Extending simulations to include non-ideal channel conditions and integrating cross-layer optimization to assess the mechanism's impact on upper-layer protocols like TCP will also enhance the robustness and applicability of the Adaptive Backoff mechanism in practical settings.

VII. Conclusion

The Adaptive Backoff mechanism addresses the limitations of traditional DCF by integrating dynamic adjustments, queue-aware prioritization, and stabilization techniques. Simulation results confirm its effectiveness in enhancing throughput and maintaining collision rates under high traffic conditions. Future research will focus on scalability, fairness, and real-world implementation.

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