Intelligent Multi-link EDCA Optimization for Delay-Bounded QoS in Wi-Fi 7

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Abstract—IEEE 802.11be (Wi-Fi 7) introduces Multi-Link Operation (MLO) as a While MLO offers significant parallelism and capacity, realizing its full potential in guaranteeing strict delay bounds and optimizing Quality of Service (QoS) for diverse, heterogeneous traffic streams in complex multi-link scenarios remain a significant challenge. This is largely due to the limitations of static Enhanced Distributed Channel Access (EDCA) parameters and the complexity inherent in cross-link traffic management. To address this, this paper investigates the correlation between overall MLO QoS indicators and the configuration of EDCA parameters and Acess Catagory (AC) traffic allocation among links. Based on this analysis, we formulate a constrained optimization problem aiming to minimize the sum of overall packet loss rates for all access categories while satisfying their respective overall delay violation probability constraints. A Genetic Algorithm (GA)-based MLO EDCA QoS optimization algorithm is designed to efficiently search the complex configuration space of AC assignments and EDCA parameters. Experimental results demonstrate that the proposed approach's efficacy in generating adaptive MLO configuration strategies that align with diverse service requirements. The proposed solution significantly improves delay distribution characteristics, and enhance QoS robustness and resource utilization efficiency in high-load MLO environments.

Index Terms—MLO, EDCA, QoS, delay bound, genetic algorithm.

I. Introduction

The IEEE 802.11be standard (Wi-Fi 7) represents a transformative advancement in wireless local area networks, driven by the growing demand for high-throughput, low-latency applications such as real-time gaming, augmented reality, and ultra-high-definition video conferencing [1]. A cornerstone feature of this standard is Multi-Link Operation (MLO) [2], which enables Multi-Link Devices (MLDs) to concurrently transmit and receive data across multiple links in distinct frequency bands. This parallelism significantly enhances throughput and supports delay-sensitive traffic. Within the Wi-Fi framework, the Enhanced Distributed Channel Access (EDCA) mechanism ensures Quality of Service (QoS) by providing differentiated access through parameters such as Arbitration Inter-Frame Space (AIFS) and Transmission Opportunity limit (TXOP) for various Access Categories (ACs). While the synergy of MLO's concurrent capabilities and EDCA's prioritization offers substantial potential for robust QoS and efficient resource utilization under high load, achieving stringent delay guarantees, particularly for end-to-end delay bounds [3], [4], remains a critical challenge in complex MLO scenarios.

Ensuring strict end-to-end delay bounds for diverse traffic streams is essential for emerging applications. However, integrating MLO with EDCA [5] poses key challenges to predictable delay performance. First, traffic management across links demands effective load balancing and cross-link interference mitigation. Second, EDCA's static parameters for its four ACs fail to adapt to dynamic patterns from varying link assignments. Under high loads, this mismatch exacerbates contention and congestion, raising delay violations for sensitive services and risking starvation of low-priority traffic. Consequently, long-tail delay distributions emerge, degrading QoS.

To address these challenges, this paper proposes a novel optimization framework for MLO networks operating in Simultaneous Transmit and Receive (STR) mode. Inspired by advancements in dynamic MAC protocols, such as the AI-MAC framework [6], our approach jointly optimizes AC-to-link traffic allocation and per-AC, per-link EDCA parameter configurations. To quantify MLO QoS, we develop an analytical model that precisely calculates delay violation probabilities. We then formulate a constrained optimization problem to minimize packet loss under strict delay constraints. Since this problem is a complex mixed-integer non-linear optimization, we use genetic algorithm (GA) to efficiently find a near-optimal solution for delay-bounded QoS. Our framework ensures robust performance in next-generation Wi-Fi networks.

The rest of this paper is organized as follows. Section II introduces the multi-link EDCA contention model. Section III analyzes the total delay of the multi-link EDCA model. Section IV analyzes the parameter sensitivity of our models and presents QoS optimization and the corresponding algorithm. Section V provides the

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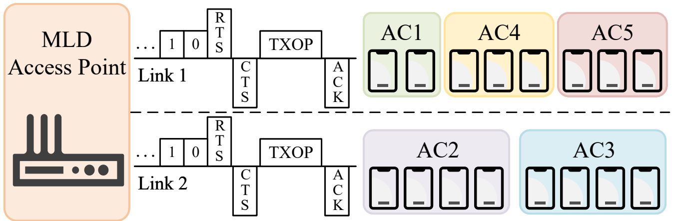

Fig. 1. Multi-link EDCA system with $M = 2$ links and AC-to-link allocation.

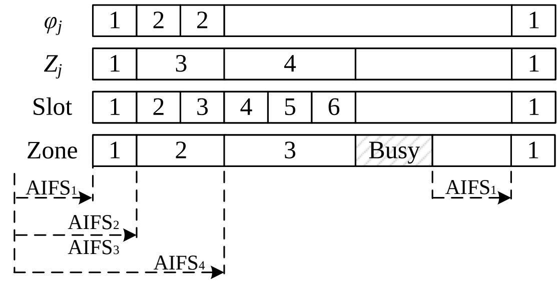

Fig. 2. The EDCA contention process within the AIFS zone model on a single link.

numerical results. Finally, we conclude this paper in Section VI.

II. System Model

We model an IEEE 802.11be MLO Basic Service Set (BSS) with M independent links in distinct frequency bands. The system includes one MLD Access Point (AP) and multiple MLD stations (STAs) with saturated traffic. We consider the STR mode, enabling MLDs to transmit on one link while receiving on another [7]. Each link uses independent channel access with RTS/CTS to reduce collisions.

The system supports I_{all} ACs, where AC_i ($i = 1, \ldots, I_{\text{all}}$) is associated with n_i^{all} STAs, each potentially carrying an uplink and a downlink AC_i flows. We analyze an AC-to-link assignment strategy, mapping all STAs with AC_i flows to a single link $m_i \in \{1, \ldots, M\}$. Fig. 1 illustrates the multi-link EDCA model for $M = 2$, $I_{\text{all}} = 5$. Each link employs the EDCA mechanism. Single $I (I \leq I_{\text{all}})$ active ACs have STAs assigned, with $n_i = n_i^{\text{all}}$ for AC_i on the link, or $n_i = 0$ otherwise. The EDCA parameters for AC_i are:

- $\text{CW}_{\min}, i$ and $\text{CW}_{\max}, i$: contention window bounds;
- AIFS_i: inter-frame spacing for priority differentiation;
- TXOP_i: channel occupancy limit;
- R_i: retry limit.

These ensure prioritized, efficient channel access. We also adjust the retry limit (R_i) to improve AC_i frame reliability.

To analyze EDCA contention with varying AIFS values among the I active ACs on this single link, we adopt the AIFS zone model [8], [9], as illustrated in Fig. 2. This model is applied to the I active ACs present on the link. It divides the backoff period following the shortest AIFS among these active ACs (denoted AIFS_1) into J time zones based on their distinct AIFS values. Each zone j represents a set of time slots where specific active ACs can compete, with Z_j denoting the number of active ACs eligible to contend in zone j. For each active AC_i on this link, we define Z_i^0 as the first zone where it can begin contending.

The zone for slot j in the backoff period after AIFS_1 is defined as:

$$\varphi_j = \max\{k \mid h_k < j - 1\}, \tag{1}$$

where $j = 1, 2, \ldots, h_I$, and h_k is the relative slot offset of the k-th AIFS value in the sorted list of the I active ACs' AIFS values on this link, given by:

$$h_k = \frac{\text{AIFS}_k - \text{AIFS}_1}{\sigma}, \tag{2}$$

with σ representing the slot time. For the zone model analysis, we assume the AIFS values of the I active ACs on the link are sorted in ascending order ($\text{AIFS}_{\min} = \text{AIFS}_1 \leq \cdots \leq \text{AIFS}_I$ in the sorted list), and the index k in these equations refers to the index in this sorted list of AIFS values (from 1 to I). Note that the set of active ACs and their corresponding parameters (n_i, AIFS_i, etc.) are specific to the link being analyzed.

III. Analytical Model for Multi-Link EDCA QoS

A. EDCA Collision Model

For each link, based on the AIFS zone model, we derive fixed-point equations to approximate the collision probability c_i and transmission probability p_i for each AC_i. These probabilities characterize contention dynamics across zones and enable performance evaluation of the EDCA mechanism.

The stationary probability of the system being in zone k, denoted by π_k, can be computed from the steady-state probabilities of the Markov chain as follows:

$$\pi_k = \begin{cases} \pi_0^0 \left[1 + \sum_{j=h_k+2}^{h_{k+1}} q_k^{j-h_k-1} \right] \alpha_{k-1}, & k \neq J, \\ \pi_0^0 (1 - q_J)^{-1} \alpha_{J-1}, & k = J, \end{cases} \tag{3}$$

where π_0^0 is the normalization constant, α_j accounts for transitions between zones, and q_k represents the probability that no station in zone k transmits. These are defined as

$$\pi_0^0 = \left(1 + \sum_{i=1}^{J-1} \sum_{j=h_i+2}^{h_{i+1}+1} q_i^{j-h_i-1} \alpha_{i-1} + \frac{q_J \alpha_{J-1}}{1 - q_J} \right)^{-1},$$

$$\alpha_j = \prod_{\ell=1}^{j} q_\ell^{h_{\ell+1}-h_\ell}, \quad \alpha_0 = 1, \quad q_k = \prod_{i=1}^{Z_k} r_i^{n_i},$$

where $r_k = 1 - p_k$ is the probability that AC_k does not transmit, and Z_k is the number of ACs contending in zone k.

Next, we compute the collision probability c_k for AC_k, which accounts for collisions in zones where AC_k is eligible to contend (from zone Z_k^0 onward):

$$c_k = \sum_{j=Z_k^0}^{J} \frac{\pi_j}{\sum_{i=Z_k^0}^{J} \pi_i} \left(1 - \frac{\prod_{l=1}^{Z_j} r_\ell^{n_\ell}}{r_k}\right), \tag{4}$$

which weights the collision likelihood in each zone by the normalized probability of AC_k being active.

The transmission probability p_k is derived using a mean-value approximation [10]:

$$p_k = \frac{2}{\eta_k \sum_{j=0}^{R_k-1} c_k^j \left(f_{k,j} - 1\right)}, \tag{5}$$

where $\eta_k = (1 - c_k)(1 - c_k^{R_k})^{-1}$ reflects the success probability over R_k retransmission attempts, and $f_{k,j} = 2^{\min\{j,m_k\}}\text{CW}_{\min,k}$ defines the contention window size at backoff stage j. Here, $m_k = \log_2(\text{CW}_{\max,k}/\text{CW}_{\min,k})$ is the maximum backoff stage, and the factor 2 models the exponential window growth.

Eq. (3)-(5) forms a fixed-point system, solved iteratively to obtain p_k and c_k for each AC_k. These probabilities enable the calculation of the packet loss probability, given by:

$$P_{loss,k} = {c_k}^{R_k}, \tag{6}$$

where packets exceeding the maximum retransmission limit R_k are discarded. This metric underpins the QoS evaluation in subsequent analyses.

B. Delay Performance

To evaluate delay performance, we model the total delay for AC_k. We derive the fundamental timing parameters for the EDCA RTS/CTS access mechanism. These parameters include the data packet transmission time $T_{\text{DATA},k}$ for AC_k, and the control frame transmission times T_{RTS}, T_{CTS}, and T_{ACK}, defined as:

$$T_{\text{DATA},k} = T_{\text{PHY\_H}} + (L_{\text{MAC\_H}} + L_k)/r_{\text{data}}, \tag{7}$$

where $T_{\text{PHY\_H}}$ is the physical layer header duration, $L_{\text{MAC\_H}}$ and L_k denote the MAC header and payload lengths for AC_k, respectively, and L_{RTS}, L_{CTS}, and L_{ACK} represent the lengths of the respective control frames. The data rate r_{data} and control rate r_{ctrl} determine the transmission rates for data and control packets, respectively.

A key parameter for delay modeling is the TXOP limit, TXOP_k. Once AC_k obtains channel access, the maximum number of data packets it can transmit within a TXOP is:

$$N_k = \max\left\{\left\lfloor \frac{\text{TXOP}_k}{\Delta_k} \right\rfloor, 1\right\}, \tag{8}$$

where $\Delta_k = T_{\text{DATA},k} + T_{\text{ACK}} + 2\text{SIFS}$, and T_{SIFS} is the Short Interframe Space duration. The floor function ensures at least one packet is sent, even for a short TXOP, accommodating bursty traffic efficiently.

Building on these, we define the collision time T_k^{C} and the successful transmission time T_k^{S} for AC_k:

$$\begin{cases} T_k^{\text{C}} = T_{\text{RTS}} + \text{AIFS}_k, \\ T_k^{\text{S}} = T_{\text{RTS}} + T_{\text{CTS}} + N_k\Delta_k + \text{SIFS} + \text{AIFS}_k, \end{cases} \tag{9}$$

where T_k^{C} reflects the time lost to an RTS collision, and T_k^{S} accounts for the full sequence of RTS, CTS, and N_k DATA-ACK exchanges.

Our objective is to compute the delay violation probability, defined as the probability that the delay of AC_k exceeds a specified threshold, i.e., $\Pr(D_k \geq D_{\max,k})$, which corresponds to the complementary cumulative distribution function (CCDF) of delay. We adopt a generating function based method from [10] to characterize the CCDF of the total delay. The delay generating function for AC_k, denoted by $\widehat{D}(z)$ (with the superscript (k) omitted for clarity), is given as follows:

$$\widehat{D}(z) = \frac{1}{N_k}\widehat{A}(z)\widehat{T}(z)\widehat{\epsilon}(z) + \frac{N_k - 1}{N_k} z^{\Delta_k/\delta}, \tag{10}$$

where z is a complex variable, δ is the discrete time slot duration, and N_k is the number of packets transmitted in a TXOP. The functions $\widehat{A}(z)$, $\widehat{T}(z)$, and $\widehat{\epsilon}(z)$ represent the generating functions for backoff and collision time, successful transmission time, and AIFS defer period, respectively. The second term captures the additional delay for subsequent packets within a TXOP, averaging the data transmission overheads.

The AIFS defer period generating function $\widehat{\epsilon}(z)$ accounts for the AC_k waiting time before contention:

$$\widehat{\epsilon}(z) = \begin{cases} z^{\text{AIFS}_k/\delta}, & k = 1, \\ \dfrac{s_{h_k} z^{\text{AIFS}_k/\delta}}{1 - \sum_{\ell=1}^{h_k} \mu_\ell z^{\tau_\ell/\delta}}, & k \neq 1, \end{cases} \tag{11}$$

where s_{h_k} is the probability of the channel remaining idle for h_k slots, μ_ℓ is the probability of an interruption at slot ℓ, and τ_ℓ is the excess delay due to interruptions, defined as:

$$\tau_\ell = \text{AIFS}_1 + (\ell - 1)\sigma + \xi_\ell, \quad s_\ell = \prod_{m=1}^{\ell}\prod_{j=1}^{\varphi_m} r_j^{n_j},$$

$$\mu_\ell = \left(\prod_{m=1}^{\ell-1}\prod_{j=1}^{\varphi_m} r_j^{n_j}\right)\left(1 - \prod_{j=1}^{\varphi_\ell} r_j^{n_j}\right),$$

The interruption duration ξ_ℓ is:

$$\begin{aligned} \xi_\ell &= \begin{cases} N_k\Delta_k - T_{\text{SIFS}}, & \text{w.p. } \rho_k(\ell), \quad 1 \leq k \leq \varphi(\ell), \\ T_{\text{C}} - \text{AIFS}_k, & \text{w.p. } 1 - \sum_{k=1}^{\varphi(\ell)} \rho_k(\ell), \end{cases} \\ \rho_k(\ell) &= \frac{n_k p_k r_k^{n_k-1} \prod_{j=1,j\neq k}^{\varphi(\ell)} r_j^{n_j}}{1 - \prod_{j=1}^{\varphi(\ell)} r_j^{n_j}}, \end{aligned} \tag{12}$$

where $\rho_k(\ell)$ is the probability that AC_k causes the interruption in zone ℓ.

The generating function for the backoff and collision time involves the AC_k is:

$$\widehat{A}(z) = \sum_{i=0}^{R_k-1} \eta_k c_k^i \widehat{C}(z)^i \prod_{j=0}^{i} \frac{1-\widehat{Y}(z)^{f_{k,j}}}{f_{k,j}(1-\widehat{Y}(z))}. \tag{13}$$

The generating function of the channel occupancy of a collision involving AC_k stations is:

$$\widehat{Y}(z) = (1-c_k)z^{\sigma/\delta} + \sum_{\ell=1}^{I} \gamma_{k,\ell}\widehat{G}_\ell(z) + \nu_k \widehat{H}(z), \tag{14}$$

where $\gamma_{k,\ell}$ is the probability that AC_k is blocked by AC_ℓ:

$$\gamma_{k,\ell} = \sum_{j=\max\{Z_k^0, Z_\ell^0\}}^{J} \frac{\pi(j)}{\sum_{i=Z_k^0}^{J}\pi(i)} \gamma_{k,\ell}(j),$$

with $\gamma_{k,\ell}(j)$ defined as:

$$\gamma_{k,\ell}(j) = \begin{cases} r_k^{n_k-1} n_\ell p_\ell r_\ell^{n_\ell-1} \prod\limits_{\substack{i=1\\ i\neq k, i\neq \ell}}^{Z_j} r_i^{n_i}, & \ell \neq k, \\ (n_k-1)p_k r_k^{n_k-2} \prod\limits_{\substack{i=1\\ i\neq k}}^{Z_j} r_i^{n_i}, & \ell = k, \end{cases}$$

and $\nu_k = c_k - \sum_{\ell=1}^{I}\gamma_{k,\ell}$ accounts for other collisions. Here, π_j is the stationary probability of zone j.

The remaining generating functions are given as:

$$\begin{aligned} \widehat{T}(z) &= z^{T_{\mathrm{DATA},k}/\delta}, \\ \widehat{H}(z) &= \widehat{C}(z) = \widehat{\epsilon}(z) z^{T_{\mathrm{C}}/\delta}, \\ \widehat{G}_\ell(z) &= \widehat{\epsilon}(z) z^{(T_{\mathrm{S},\ell} - \mathrm{AIFS}_k - \mathrm{SIFS})/\delta}, \end{aligned} \tag{15}$$

where, $\widehat{T}(z)$ captures the delay for a successful transmission, $\widehat{C}(z)$ and $\widehat{H}(z)$ capture collision delays, and the function $\widehat{G}_\ell(z)$ captures the delay experienced by AC_k due to blocking from AC_ℓ.

Based on the total delay generating function in Eq. 10, the CCDF of the total delay is obtained through numerical inversion of generating function, using the Fourier-series method proposed in [11]:

$$\begin{aligned} \Pr(D_k \geq x) &= \frac{1}{2\pi r^x}\int_0^{2\pi} \frac{1-\widehat{D}(re^{\mathrm{i}u})e^{-\mathrm{i}xu}}{1-re^{\mathrm{i}u}} du \\ &\approx \frac{1}{2Nr^x}\sum_{n=-N}^{N-1} \frac{1-\widehat{D}\left(re^{-\mathrm{i}\pi n/N}\right)e^{\mathrm{i}\pi n/l}}{1-re^{-\mathrm{i}\pi n/N}}, \end{aligned} \tag{16}$$

where $r \in (0,1)$ is a scaling factor, x is the integer delay threshold in units of δ, and l determines the summation range via $N = xl$. This approximation is accurate for large x, where the tail distribution exhibits exponential decay. As mentioned in [11], setting $l = 1$ and $r = 10^{-8/v}$ yields numerical errors smaller than 10^{-16}.

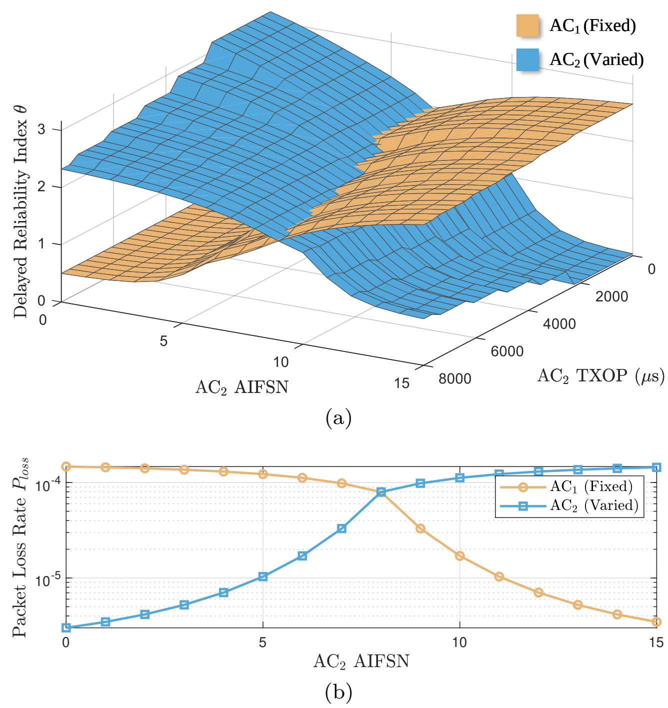

Fig. 3. The parameter sensitivity of EDCA: (a) impact to delay reliability index, (b) impact of packet loss probability.

To evaluate delay performance, we define the delay reliability index θ_k for AC_k:

$$\theta_k = -\log\{\Pr(D_k \geq D_{max,k})\}, \tag{17}$$

where $D_{\max,k}$ is the delay threshold for AC_k. A higher θ_k indicates a lower probability of violating the delay constraint, reflecting greater reliability for QoS-sensitive applications.

IV. Multi-Link EDCA Optimization

In this section, we present a genetic algorithm-based approach to optimize multi-link EDCA performance by dynamically adjusting contention parameters, aiming to balance delay and packet loss across ACs under varying traffic conditions.

A. Parameters Sensitivity

To guide the optimization, we first analyze the sensitivity of QoS metrics to key parameters. In EDCA, parameter selection not only affects performance directly but also influences the interaction between mechanisms. This section analyzes the impact of two newly introduced parameters in EDCA: AIFS and TXOP. And we represent the AIFS by AIFSN (AIFS Number) = (AIFS − SIFS)/σ.

We evaluate a scenario with two ACs: AC_1 configured as $\mathrm{AIFSN}_1 = 8$ and $\mathrm{TXOP}_1 = 4080$ μs while AC_2 has AIFSN_2 varying from 2 to 15 and TXOP_2 ranging from 0 to 8160 μs. Other parameters are identical for both AC_1 and AC_2: $\mathrm{CW}_{\min} = 32$, $\mathrm{CW}_{\max} = 1024$, retransmission limit $R = 7$, number of stations $n = 4$, packet size $L = 1000$ bytes, and maximum tolerable delay $D_{max} =$

100 ms. Fig. 3a shows the delay reliability index θ under various AIFSN_2 and TXOP_2 settings, and Fig. 3b shows the packet loss probability P_{loss} versus AIFSN_2.

In Fig. 3a, although AC_1's parameters remain fixed, its delay violation probability is affected by AC_2's settings. As AIFSN_1 increases, the delay reliability index of AC_1 drops, while that of AC_2 decrease. Further analysis reveals that TXOP has different effects depending on AIFSN. When AIFSN is small, a large TXOP allows one station to occupy the channel longer, blocking others and increasing delay. In contrast, when AIFSN is large, increasing TXOP mitigates contention and improves delay performance.

Figure 3b complements this by showing that when AIFSN_2 approaches AIFSN_1 in Fig. 3a, a balance in delay performance emerges between ACs, a shorter multi-station conflict time will lower the overall delay. However, increased contention leads to fewer blocks but higher collision rates, significantly raising the packet loss probability.

This parameter analysis shows that effective QoS evaluation must consider not only the fulfillment of meeting delay-reliability constraints but also the impact on packet loss to ensure balanced and stable system performance. Optimizing delay alone may increase contention and result in higher packet loss rates.

B. Delay Bound QoS Optimization Problem

To optimize the QoS performance of EDCA, we formulate a constrained optimization problem. To minimize the total packet loss probability across all ACs while ensuring that each AC's delay violation probability remains below a specified threshold, the optimization framework treats all ACs equally by default but can be extended to prioritize specific ACs through the incorporation of weighted factors.

$$\begin{aligned} \mathbf{P1}: \quad & \arg\max_{\mathbf{x}_i, i\in I_{\text{all}}} \sum_{i=1}^{I_{\text{all}}} -\log(P_{loss,i}) \\ & \text{s.t. } \Pr(D_i \geq D_{max,i}) < \epsilon_i, 1 \leq i \leq I_{\text{all}}, \end{aligned} \tag{18}$$

where $\mathbf{x}_i$ is the parameter vector of AC_i, including $\text{CW}_{\min,i}$, $\text{CW}_{\max,i}$, AIFSN_i, TXOP_i, and R_i. The constraint ensures that the delay violation probability for each AC does not exceed its threshold ϵ_i, addressing the diverse QoS requirements of different ACs.

The retransmission limit R_i is treated as a variable, as it directly impacts both packet loss and delay, as modeled in Eq. (6) and Eq. (13). Based on IEEE 802.11 standards, these parameters have pre-defined ranges: $\text{CW}_{\min,i}$ and $\text{CW}_{\max,i}$ range from 1 to 1023 with $\text{CW}_{\min,i} \leq \text{CW}_{\max,i}$, AIFSN_i from 2 to 15, TXOP_i from 0 to 8.192 ms with a step size of 32 μs, and R_i from 4 to 7. These bounds define the feasible parameter space for optimization, balancing delay and loss under varying network conditions.

The optimization problem's large, discrete, and non-convex parameter space renders exhaustive search computationally infeasible. We therefore adopt a genetic algorithm (GA), a powerful heuristic whose population-based search is particularly adept at exploring the vast solution space to avoid local optima. While GA does not guarantee global optimality, its key hyperparameters were empirically tuned for robust performance, and its practical convergence for this problem is demonstrated in our results.

Algorithm 1 Genetic Algorithm for EDCA Parameter Optimization

Initialize environment and define parameter ranges for AIFSN, $\text{CW}_{\min}$, $\text{CW}_{\max}$, TXOP, and R.
Set fixed parameters: I_{all}, n, $D_{\max}$, ϵ.
Set genetic algorithm parameters: population size N_{pop}, maximum generations N_{gen}, crossover rate β_{cross}, elite count N_{elite}, and early stopping threshold N_{stag}.
Define fitness function: compute all $P_{loss,i}$ and return $\sum_{i=1}^{I_{\text{all}}} -\log(P_{loss,i})$.
Define constraints: $\Pr(D \geq D_{\max}) - \epsilon \leq 0$.
Run genetic algorithm:
Initialize population within parameter bounds.
for each generation **do**
    Evaluate fitness for each individual.
    Apply selection to choose parents.
    Perform crossover and mutation to generate offspring.
    Preserve elite individuals.
    Update population.
end for
Decode optimal solution $P_{loss}, \Pr(D \geq D_{\max})$ and output parameters.

For EDCA parameter tuning, the proposed GA minimizes packet loss while satisfying delay constraints, as outlined in Algorithm 1. It initializes diverse parameter sets, evolves them via selection, crossover, and mutation, and retains elite solutions to converge to a near-optimal configuration. A fitness function prioritizing low packet loss enhances adaptive QoS and robustness in high-load scenarios.

V. Results and Discussion

In this section, we present the simulation results of the proposed QoS optimization method. We compare the performance of three distinct scenarios: the optimized multi-link EDCA parameters, the optimized single-link EDCA parameters, and the single-link EDCA using default parameters.

The parameter settings in the simulation are summarized in Table I unless otherwise specified or varied.

To evaluate the proposed GA for optimizing multi-link EDCA parameters, we conducted simulations using a BSS with five ACs, each configured with distinct QoS requirements. We set the number of stations for every AC $n = [2, 4, 4, 3, 3]$, packet sizes $L =$

TABLE I
Simulation Parameters

Parameter	Value	Definition
r_{ctrl}	1 Mbps	Control rate for conventional channel
r_{data}	11 Mbps	Data rate for conventional channel
σ	20 μs	Slot time duration
δ	10 μs	Discrete time slot
T_{SIFS}	10 μs	SIFS (Short Interframe Space) time
$T_{\text{PHY\_H}}$	192 μs	Physical layer header time
L_{RTS}	160 bits	R-RTS frame length
L_{CTS}	112 bits	R-CTS frame length
L_{ACK}	112 bits	ACK frame length
$L_{\text{MAC\_H}}$	224 bits	MAC layer header length
N_{pop}	2000	Population size
N_{gen}	500	Maximum generations
N_{elite}	80	Elite count
N_{cross}	0.8	Crossover rate
N_{stag}	50	Early stopping threshold

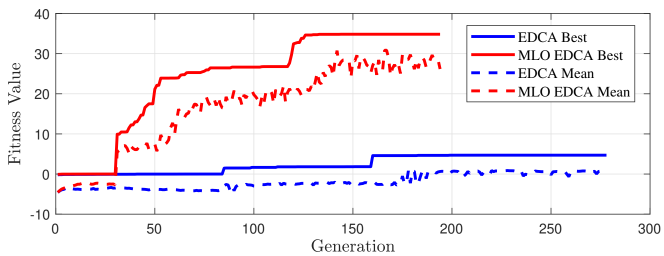

Fig. 4. Fitness function convergence for MLO and Single-Link EDCA Optimization.

$[50, 210, 256, 800, 2000]$ bytes, maximum tolerable delays $D_{\max} = [50, 60, 100, 300, 300]$ ms, and delay violation probability thresholds $\epsilon_i = [10^{-7}, 10^{-6}, 10^{-4}, 10^{-2}, 0.5]$. These settings reflect a diverse traffic mix, with AC_1 and AC_2 representing delay-sensitive services, AC_3 for streaming, and AC_4 and AC_5 for best-effort and background traffic.

Figure 4 shows the fitness function convergence over generations for the genetic algorithm applied to both multi-link EDCA optimization (MLO EDCA) and single-link EDCA optimization (EDCA). This figure shows the algorithm's efficiency in minimizing packet loss under delay constraints. The curves for both best and mean fitness values converge quickly. They stabilize at near-optimal levels.

Figure 5 compares the QoS performance across the five ACs for three distinct configurations: the default single-link EDCA settings, the optimized single-link EDCA parameters found by the GA, and the optimized multi-link EDCA configuration found by the GA. Fig. 5a illustrates the delay violation probability $\Pr(D \geq D_{\max})$, showing that both optimized configurations significantly reduce violations compared to the default settings. Similarly, Fig. 5b shows the packet loss probability P_{loss}. The optimized multi-link EDCA configuration significantly outperforms single-link EDCA configurations, achieving the lowest loss rates and ensuring enhanced reliability for time-critical applications.

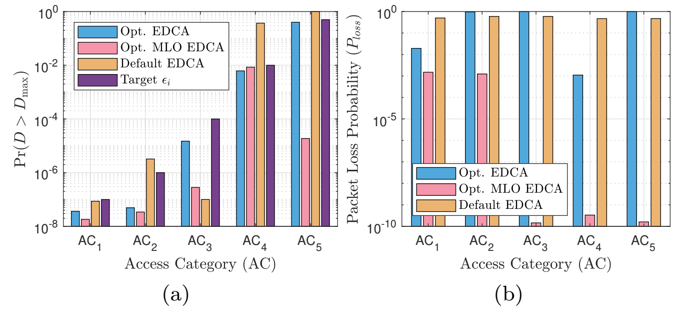

Fig. 5. Comparison of QoS performance for Default EDCA, Optimized EDCA, and Optimized MLO EDCA: (a) delay violation probability, (b) packet loss probability.

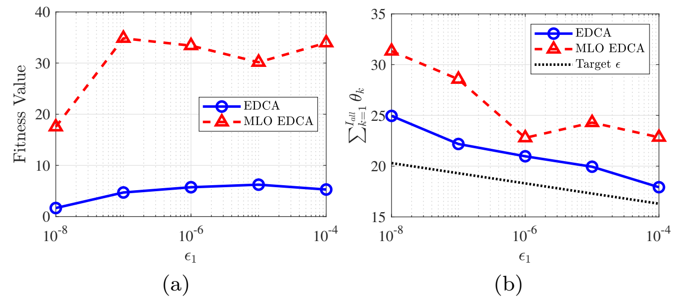

Fig. 6. Impact of target ϵ_1 on QoS performance of Optimized EDCA and Optimized MLO EDCA: (a) fitness value, (b) sum of reliability index.

Figure 6 shows how the target reliability constraint of AC_1 (ϵ_1) influences the QoS performance of the optimized EDCA and multi-link EDCA configurations. As shown in Fig. 6a, the fitness value does not increase monotonically, reflecting a trade-off between fitness and reliability in both Fig. 6a and Fig. 6b. Moreover, the fitness value is consistently higher for multi-link EDCA, owing to its ability to leverage multiple links for improved reliability. These findings highlight the complex relationship between performance optimization and reliability constraints in multi-link network configurations.

VI. Conclusion

In this paper, we addressed the critical challenge of guaranteeing strict delay bounds for QoS in IEEE 802.11be MLO STR networks. We propose an optimization framework utilizing an analytical model and a genetic algorithm. This framework jointly optimizes AC traffic allocation among links and per-link EDCA parameter configurations to minimize overall packet loss while satisfying delay violation probability constraints. Our evaluation demonstrates that this approach effectively identifies viable configurations that satisfy stringent delay constraints while achieving significant performance gains. Future work will explore QoS performance optimization in various MLO working scenarios, including unsaturated burst conditions and hardware-based studies.

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