Performance Modeling of Multi-Link Operation in Wi-Fi 7 Networks

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***Abstract*—This paper presents analytical models for characterizing Wi-Fi connection behavior and evaluating Quality of Service (QoS) performance in Multi-Link Operation (MLO) schemes for Wi-Fi 7 networks. The models estimate the probability distribution of Wi-Fi link visits and derive three key QoS metrics: expected download failure volume, deadline miss ratio, and QoS satisfaction probability. Their accuracy is validated against custom-developed simulations, demonstrating close alignment with empirical results. To assess the feasibility of the proposed models, we compare three MLO schemes—MLSR, MLMR-dual, and MLMR-triple—with a baseline Multipath Offloading (MO) scheme proposed in prior work. Numerical results show that the MLMR-triple-link configuration consistently outperforms the MO baseline, reducing download failures and deadline misses by up to 90% and 68%, respectively. The proposed framework lays a solid analytical foundation for next-generation wireless access strategies, supporting intelligent and adaptive MLO design potentially guided by AI-driven link aggregation and QoS optimization in future Wi-Fi 7 deployments.**

***Index Terms*—Wi-Fi 7, Multi-Link Operation (MLO), Analytical Modeling, QoS Performance, Wireless Networks**

I. Introduction

Wi-Fi (WiFi) has become a ubiquitous communication medium in both home and institutional environments, serving as the backbone for accessing media streaming, cloud services, and interactive applications [1]. The growing demand for these services places increasing pressure on wireless networks to meet stringent Quality of Service (QoS) requirements [2]. To address this, one prominent solution is Multipath TCP (MPTCP), a standard proposed by the Internet Engineering Task Force (IETF), which enables simultaneous data transmission across multiple interfaces [3]. This technique, often referred to as Multipath Offloading (MO), enhances bandwidth aggregation and provides greater resilience to delay, particularly in heterogeneous network environments.

Prior studies have examined MO in WiFi 5 (IEEE 802.11ac) and WiFi 6 (IEEE 802.11ax) environments. Bhooanusas and Sou [4] applied a Markov chain model [5] to capture the stochastic behavior of WiFi links under MO, comparing offload volume and deadline miss ratio with the earlier work by Sou and Peng [6] to show closer alignment with real-world conditions. Zhuo, Gao, Cao, and Hua [7] proposed an auction-based incentive framework to encourage delay-tolerant cellular users to allocate their bandwidth to WiFi hotspots in exchange for greater WiFi access, while Pisupati and Ramaiyan [8] simulated WiFi link dynamics focusing on signal quality and noise aggregation. However, these standards are limited to single-radio interfaces, which often degrade QoS under congestion and fluctuating link conditions [9], [10].

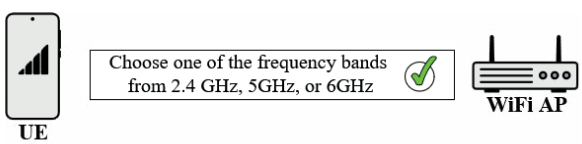
WiFi 7 (IEEE 802.11be) introduces Multi-Link Operation (MLO), which enables simultaneous transmissions across multiple radio channels [10]–[12]. This architectural advancement offers significant improvements in QoS metrics such as throughput, latency, and reliability, making it especially beneficial in high-demand and dynamic environments. More importantly, MLO supports emerging applications with intensive bandwidth requirements (e.g., real-time gaming and etc.). In response, recent research has increasingly focused on optimizing MLO mechanisms to fully leverage these capabilities.

Zhang et al. [12] proposed a two-stage algorithm involving AP-STA pairing, WiFi Access Point (AP) identifies the most suitable stations based on current link conditions, and dynamic radio interface selection, with the aim of improving network throughput under heterogeneous station capabilities. Simulation results showed significant gains over single-link operation. Complementing this, Korolev, Levitsky and Khorov [11] developed an analytical model that extended Bianchi's model [13] to analyze Simultaneous Transmit-and-

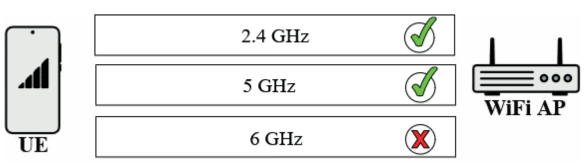
Receive (STR) and non-STR MLO modes, revealing significant throughput gains for STR. In addition, Lian, Tong, and Fu [14] proposed an unsupervised learning framework that formulates the task as a Multi-Armed Bandit (MAB) problem. The scheme first identified the most promising arm and then applied Monte Carlo Tree Search to find the best channel. The simulation results showed that their proposed method outperformed the standard baselines in both throughput and selection accuracy.

In this paper, we propose analytical models to characterize the stochastic process of MLO to address QoS issues in WiFi 7 networks. Our objective is to utilize these models to assess QoS performance, which has received limited attention in the existing literature. The state of the WiFi connection during a user session time is modeled using a Markov chain framework. To validate the precision of the proposed models, we compare the theoretical distribution of the number of WiFi visits per selected link with the simulation results. Furthermore, we assess the effectiveness of the proposed approach by evaluating three key QoS metrics (e.g., average download failure volume $E[V_F]$, deadline miss ratio P_{miss}, and QoS satisfaction P_{QoS}) under various network conditions. These results are compared across the Multi-Link Single-Radio (MLSR), Multi-Link Multi-Radio (MLMR) dual-link, and triple-link schemes, as well as the baseline MO model presented in [6].

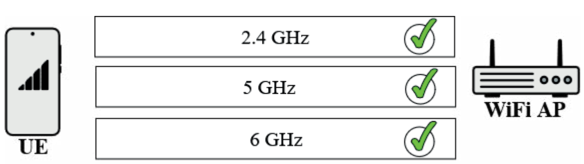
The rest of this paper is organized as follows. Section II presents the system model and analytical framework. Section III validates the model via simulation. Section IV provides QoS evaluations under various configurations. Section V concludes and outlines future research directions.



(a) MLSR.



(b) MLMR with Dual Band.



(c) MLMR with Triple Band.

Fig. 1: An illustration of MLO in WiFi 7.

II. System Model

WiFi 7 introduces the MLO feature to mitigate QoS degradation by enabling mobile users to aggregate multiple radio links concurrently during transmission sessions [10]. When multiple radios are used, the mode is called MLMR. If only one radio is active, it is known as MLSR. The WiFi 7 AP controller dynamically switches between these modes based on network conditions and device capabilities. This section will present an overview of MLO, a stochastic model for WiFi link visits, and derived QoS metrics under the proposed framework.

A. *Multi-link operation in WiFi 7 networks*

Fig. 1 illustrates various types of MLO supported in WiFi 7. In the MLSR mode, the WiFi AP controller allocates only one of the three available frequency bands (2.4 GHz, 5 GHz, or 6 GHz) to the STA, as shown in Fig. 1a. When the STA resides in an area where multiple channels are available, the AP can instead operate in the MLMR mode, selecting two or all three bands (see Figs. 1b and 1c).

In MLMR, the AP can assign transmission (Tx) and reception (Rx) functions across different radio links. For example, the primary link may be designated for Tx, while secondary links handle both Tx and Rx. When these operations are performed simultaneously, the mode is referred to as STR. Conversely, in the non-STR mode, the AP cannot perform Tx and Rx at the same time during a session.

In this paper, we focus on evaluating the downlink QoS performance where the user device leverages the MLO capability for data reception. Therefore, we consider the Tx-side behavior under the non-STR scenario. Since WiFi 7 radio links operate independently, we model the stochastic behavior of WiFi link usage during a download session on a per-link basis, which will be detailed in the next section.

B. *Stochastic Modeling of WiFi Link Visits*

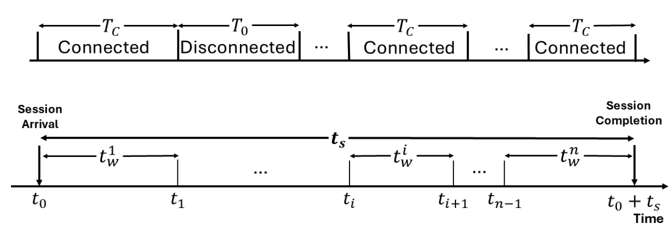


Fig. 2: Timing diagram for the distribution of WiFi connection time t_w where $X(t_0) = 1$ and $X(t_0 + t_s) = 1$.

As illustrated in Fig. 2, each WiFi radio interface alternates between `connected` and `disconnected` states over time. These state transitions are modeled using two random variables: T_c, representing the duration of a connected period, and T_0, representing the duration of a disconnected period.

To formally describe the link state over time, we define a stochastic process $\{X(t), t \geq 0\}$, where the state variable $X(t)$ is given by:

$$X(t) = \begin{cases} 0, & \text{the session is in the } \texttt{Disconnected} \text{ state} \\ 1, & \text{the session is in the } \texttt{Connected} \text{ state} \end{cases} \tag{1}$$

C. Derivation of WiFi visit distribution

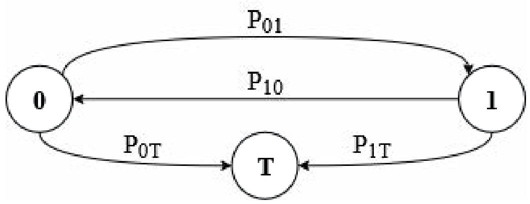


Fig. 3: A state space of $X(t)$.

We consider that a user initiates a download session at time t_0 and ends at $t_0 + t_s$, where the session duration is denoted as t_s. We assume $X(t_0) = 1$ and $X(t_0 + t_s) = 1$, indicating that the session begins while the User Equipment (UE) is in a `connected` state and also ends the same state. To generalize possible connection patterns during the session, we classify the connection state transitions between t_0 and $t_0 + t_s$ into the following four scenarios:
Condition 1: $X(t_0) \geq 1$ and $X(t_0 + t_s) \geq 1$
Condition 2: $X(t_0) \geq 1$ and $X(t_0 + t_s) = 0$.
Condition 3: $X(t_0) = 0$ and $X(t_0 + t_s) \geq 1$.
Condition 4: $X(t_0) = 0$ and $X(t_0 + t_s) = 0$.

During such an activity, the UE intermittently connects to the WiFi network a total of n times. We first formulate a discrete-time Markov chain Y_n (DTMC) with the state space $\{0, 1, T\}$ (see Fig. 3), where each state represents `disconnected`, `connected`, and `terminate`, respectively.

To derive the distribution of the number of WiFi visits before termination, we apply the Markov chain framework [5], which requires the initial probability of the WiFi starting in state i, denoted P_i, and the m-step transition probabilities before absorption into the terminating state T, denoted P_{i_{j-1},i_j}, where $j = 1, 2, \ldots, m$. Let k be the index of a specific connection pattern, and let m be the number of state changes. Then, the probability of observing the k-th connection pattern involving n visits to the `connected` state can be written as:

$$P_k(n) = P_i \cdot \prod_{j=1}^{m} P_{i_{j-1},i_j} \cdot P_{i_m,T} \tag{2}$$

To illustrate this formula, consider the case where the user connects to the WiFi exactly $n = 2$ times before termination. Let $k = 2$ represent a specific connection pattern (Condition 2). In this setting, the WiFi session starts in the `connected` state and switches between states 0 and 1 three times before reaching termination. Referring to (2), we have $m = 3$, and the corresponding pattern probability, denoted $P_2(2)$, is given by:

$$P_2(2) = P_1 \cdot P_{10} \cdot P_{01} \cdot P_{10} \cdot P_{0T} \tag{3}$$

It can be seen that the distribution of visiting 2 times can be rewritten as:

$$P_2(2) = P_1 \cdot (P_{10})^2 \cdot P_{01} \cdot P_{0T} \tag{4}$$

In addition, the probability of WiFi visit of the connection pattern $P_2(n)$ can be generalized as:

$$P_2(n) = P_1 \cdot (P_{10})^n \cdot (P_{01})^{n-1} \cdot P_{0T} \tag{5}$$

The probabilities of $P_k(n)$ for all values of k (representing different connection start/end patterns) with n WiFi visits can be defined in a similar fashion, summarized as:

$$\begin{cases} P_1(n) = (P_1)\,(P_{10} \cdot P_{01})^{n-1}\,(P_{1T}) \\ P_2(n) = (P_1)\,(P_{10})^{n}\,(P_{01})^{n-1}\,(P_{0T}) \\ P_3(n) = (P_0)\,(P_{01})^{n}\,(P_{10})^{n-1}\,(P_{1T}) \\ P_4(n) = (P_0)\,(P_{01} \cdot P_{10})^{n}\,(P_{0T}) \end{cases} \tag{6}$$

Let N_1 be the total number of times that WiFi visits the `connected` state. The probability of exactly n visits, denoted by $\Pr[N_1 = n]$, can be computed by summing the probabilities across all four patterns. Thus, we have:

$$\begin{aligned} \Pr[N_1 = n] = P(n) &= \sum_{k=1}^{4} P_k(n) \\ &= P_1(n) + P_2(n) + P_3(n) + P_4(n) \end{aligned} \tag{7}$$

Referring to Fig. 2, the connected time T_c and disconnected time T_0 have an exponential distribution with rate λ_c and λ_0, respectively. Meanwhile, the user session time t_s also utilizes an exponential distribution with rate μ. Hence, the expected values for each duration can be defined as follows.

$$E[T_c] = \frac{1}{\lambda_c}, E[T_0] = \frac{1}{\lambda_0}, E[t_s] = \frac{1}{\mu} \tag{8}$$

To formulate the DTMC for each transition probability, we refer to Fig. 3. When the state of `disconnected` is visted, after T_0, there are two ways that the `disconnected` will go next including those of `connected` and `terminate`. By this way, the transition probability that the `disconnected` state shifts to that of `connected`, denoted by P_{01}. can be derived as:

$$\begin{aligned} P_{01} &= \frac{E[T_c]}{E[T_c] + E[t_s]} \\ &= \frac{\frac{1}{\lambda_c}}{\frac{1}{\lambda_c} + \frac{1}{\mu}} = \frac{\mu}{\lambda_c + \mu} \end{aligned} \tag{9}$$

We use the same concept to define other transition probability derivations, and accordingly the total transition probability can be summarized as

$$\begin{aligned} P_{01} &= \frac{\mu}{\lambda_c + \mu}, \quad P_{0T} = \frac{\lambda_c}{\lambda_c + \mu}, P_{T,T} = 1 \\ P_{10} &= \frac{\mu}{\lambda_0 + \mu}, \quad P_{1T} = \frac{\lambda_0}{\lambda_0 + \mu} \end{aligned} \tag{10}$$

For the initial probability, we apply the renewal theory [5] in which the user will start the session with the WiFi connection by $X(t_0) \geq 1$, defined as:

$$\begin{aligned} P_1 &= \frac{E[T_c]}{E[T_0] + E[T_c]} = \frac{1/\lambda_c}{(1/\lambda_c) + (1/\lambda_0)} = \frac{\lambda_0}{\lambda_0 + \lambda_c} \\ P_0 &= (1 - P_1) = \frac{\lambda_c}{\lambda_0 + \lambda_c} \end{aligned} \tag{11}$$

Therefore, (6) can be rewritten by substituting those in (10) and (11) and then we have

$$\begin{cases} P_1(n) = \left(\frac{\lambda_0}{\lambda_0+\lambda_c}\right)\left[\frac{\mu}{(\lambda_0+\mu)(\lambda_c+\mu)}\right]^{n-1}\left(\frac{\lambda_0}{\lambda_0+\mu}\right) \\ P_2(n) = \left(\frac{\lambda_0}{\lambda_0+\lambda_c}\right)\left(\frac{\mu}{\lambda_0+\mu}\right)^{n}\left(\frac{\mu}{\lambda_c+\mu}\right)^{n-1}\left(\frac{\lambda_c}{\lambda_c+\mu}\right) \\ P_3(n) = \left(\frac{\lambda_c}{\lambda_0+\lambda_c}\right)\left(\frac{\mu}{\lambda_c+\mu}\right)^{n}\left(\frac{\mu}{\lambda_0+\mu}\right)^{n-1}\left(\frac{\lambda_0}{\lambda_0+\mu}\right) \\ P_4(n) = \left(\frac{\lambda_c}{\lambda_0+\lambda_c}\right)\left[\frac{\mu}{(\lambda_0+\mu)(\lambda_c+\mu)}\right]^{n}\left(\frac{\lambda_c}{\lambda_c+\mu}\right) \end{cases} \tag{12}$$

D. Applying the Distribution of Total WiFi Time t_w

To support the evaluation of key QoS metrics in this study, we incorporate the cumulative distribution function (CDF) of the total WiFi connection time, t_w, which was derived in our earlier work [4], [6]. While the closed-form expression of $F_W(t)$ remains unchanged, it is now used in conjunction with the newly revised connection probabilities, $P_k(n)$ given in (7) and (12). This integration enables the analysis of session-level performance under the WiFi 7 MLO scenario.

For completeness, the CDF expression is recalled below:

$$F_W(t) = \sum_{n=1}^{\infty}\sum_{j=1}^{n-1} e^{-(\lambda_c+\mu)t}\frac{[(\lambda_c+\mu)t]^j}{j!}P(n) \tag{13}$$

E. Deriving the total WiFi data rate, $B(t)$

As shown in Fig. 1, the three radio channels in WiFi 7 can operate independently and concurrently during the download session period. During this period, multi-link connections are simultaneously established, and enable the aggregation of WiFi data rates from all available links. Let $X_i(t)$ be the connection state space of WiFi channel i. The aggregated WiFi bandwidth, $B(t)$, can be then computed as:

$$B(t) = b_1(t)X_1(t) + b_2(t)X_2(t) + b_3(t)X_3(t) \tag{14}$$

Where $B(t)$ represents the total achievable WiFi data rate at time t, while $b_i(t)$ is the individual link data rate from channel i. Referring to (1), $X_i(t) \in \{0, 1\}$ reflects whether channel i is actively connected.

F. Deriving the volume of downloading failure, V_F

In this paper, we derive the three important QoS metrics including the download failure volume V_F, the deadline miss ratio P_{miss}, and the QoS satisfaction P_{QoS}.

During the download session period t_s, the user initiates the session at $t = \mathcal{T}_0$ and ends it at $t = \mathcal{T}_0 + t_s$. Thus, the amount of downloaded data depends on the aggregated bandwidth $B(t)$.

As described in previous subsections, let $f_s(t_s)$ be the density function of t_s. Since the session time follows an exponential distribution with rate μ, we have

$$f_s(t_s) = \mu e^{-\mu t_s} \tag{15}$$

Hence, the session duration t_s is a random variable drawn from this exponential distribution, while the aggregated WiFi bandwidth $B(t)$ depends on the connectivity states $X_i(t)$ of the WiFi channels.

The volume of successfully downloaded data, denoted by V_D, can then be computed by:

$$V_D = \int_{t_s=0}^{\infty}\int_{t=\mathcal{T}_0}^{\mathcal{T}_0+t_s} B(t) f_s(t_s)\, dt\, dt_s \tag{16}$$

Accordingly, the download failure volume V_F, defined as the portion of data not successfully delivered during the session, is calculated by:

$$V_F = F - V_D \tag{17}$$

where F is the original file size or content volume to be delivered.

G. Deriving the deadline miss ratio, P_{miss}

At the end session, if $V_D < F$, it means that a user fails to complete the required volume within the user session time. The deadline miss ratio, denoted as P_{miss}, is defined as the probability that the accumulated downloaded volume, V_D, falls short of the target volume F. That is,

$$P_{\text{miss}} = Pr\left(\int_{\mathcal{T}_0}^{\mathcal{T}_0+t_s} B(t)\,dt < F\right) \tag{18}$$

This expression captures the probability that the total delivered data, governed by the time-varying aggregated WiFi bandwidth $B(t)$, is insufficient over the session period t_s.

To account for the stochastic nature of t_s, we reformulate (18) by integrating over all possible session durations. Using the exponential density function, the probability becomes:

$$P_{\text{miss}} = \int_{t=0}^{\infty} Pr\left(\int_{\mathcal{T}_0}^{\mathcal{T}_0+t} B(u)\,du < F\right) f_s(t)\,dt \tag{19}$$

This deadline miss ratio, P_{miss}, serves as a fundamental QoS metric for performance evaluation under the WiFi 7 MLO environment, where multi-radio transmissions and dynamic bandwidth fluctuations significantly influence session-level reliability.

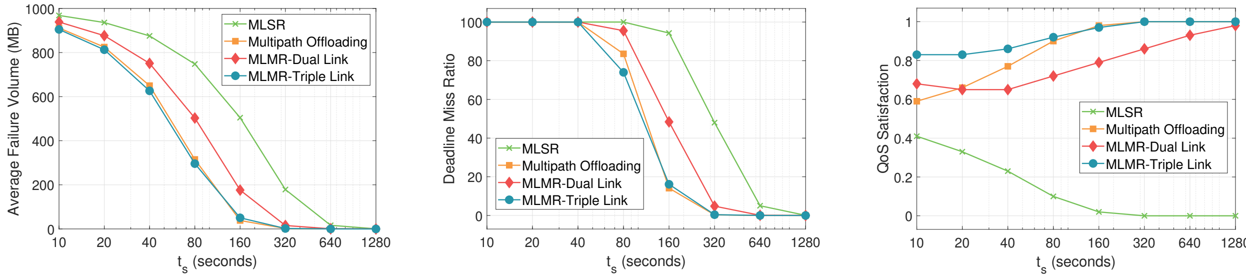
H. Deriving the QoS satisfaction, P_{QoS}

To evaluate the QoS satisfaction, P_{QoS}, we first define the average throughput achieved during the session period, denoted by $\bar{B}$. In WiFi 7 with multi-link operation, the instantaneous available bandwidth $B(t)$ fluctuates with link connectivity. The session-average throughput can therefore be expressed as:

$$\bar{B} = \mathbb{E}\left[\frac{1}{t_s}\int_{t=\mathcal{T}_0}^{\mathcal{T}_0+t_s} B(t)\right] dt \tag{20}$$

This metric represents the mean download rate that a user experiences throughout the session. To determine whether a session meets the QoS requirements, we compare $\bar{B}$ to a predefined minimum throughput threshold $B_{\min}$. Accordingly, the QoS satisfaction indicator is defined by:

$$P_{\text{QoS}} = \begin{cases} 1, & \bar{B} \geq B_{\text{min}} \\ 0, & \text{Otherwise} \end{cases} \tag{21}$$



(a) Average Failure Volume. (b) Deadline Miss Ratio. (c) QoS Satisfaction.

Fig. 4: The output metrics against user session time, t_s

Here, $P_{\text{QoS}} = 1$ indicates that the session satisfies the QoS requirement, while $P_{\text{QoS}} = 0$ indicates that the QoS guarantee is not met.

III. Model Evaluation

In this section, we validate the proposed analytical models by comparing them with simulation results obtained by means of a self-written program in the Go programming language. The theoretical distribution of WiFi link visits is computed using (7)–(12) and is compared against simulation outcomes, which estimate the probability that the WiFi connection is visited n times, denoted by $Pr[N_1 = n]$. The network is configured with average durations: $E[T_c] = 400$ seconds, $E[T_0] = 200$ seconds, and $E[t_s] = 250$ seconds, assuming exponential distributions for all time intervals. The simulation runs over 100,000 iterations.

TABLE I: Comparison of simulation and analytical results where $E[t_s] = 250$, $E[T_0] = 200$ and $E[T_c] = 2E[T_0]$

$Pr[N_1 = n]$	Simulation	Analysis	Diff %
0	0.12885	0.12821	0.4967%
1	0.63247	0.63336	0.1407%
2	0.17311	0.17323	0.0693%
3	0.04739	0.04738	0.0211%
4	0.01329	0.01296	2.4830%
5	0.00344	0.00354	2.9069%
6	0.00097	0.00099	2.0618%
7	0.00026	0.00027	3.8461%
8	0.00006	0.00007	16.6667%

Table I shows that the analytical models align closely with simulation results for the distribution of WiFi link visits per session. The peak occurs at $Pr[N_1 = 1] \approx 0.63$ in both methods, as longer connection periods ($E[T_c] = 400$) relative to disconnection ($E[T_0] = 200$) reduce the chance of multiple transitions. As n increases, probabilities drop sharply (e.g., $Pr[N_1 = 3] \approx 0.0474$, $Pr[N_1 = 5] \approx 0.0035$, $Pr[N_1 = 8] \approx 0.0007$), reflecting the rarity of frequent reconnections.

Overall, the analytical results closely match the simulation outcomes. The average percentage difference across all values of n is just 3.58%, with a maximum deviation of 16.67% at $n = 8$ (outlier). These results confirm the validity and accuracy of the proposed analytical models for predicting WiFi link visit behavior under exponential connection dynamics.

TABLE II: Default network parameters in the experiments

Parameter Name	Values
t_s (User session Time)	160 s
$E[T_c]$ (Expected WiFi connection time)	50 s
$E[T_0]$ (Expected WiFi disconnection time)	50 s
$E[F]$ (Expected file size)	1 GB
B_{min} (Guaranteed minimum bandwidth)	40 Mbps
$E[B]$ (Expected total bandwidth)	50 Mbps
Simulation iteration	100,000

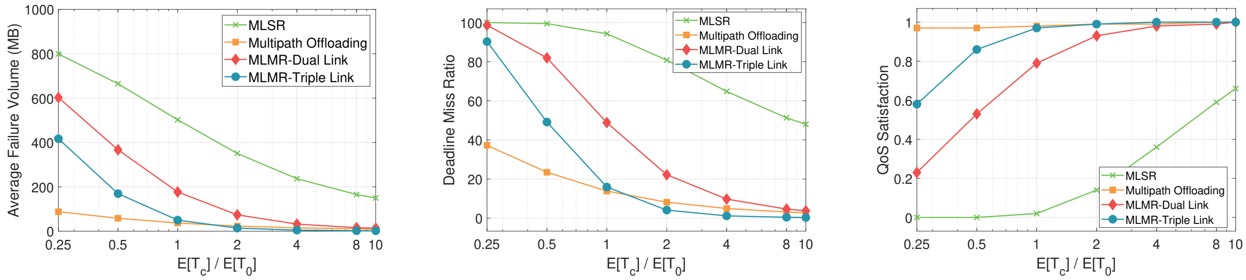
IV. Numerical Examples

To evaluate the feasibility of the proposed analytical models in capturing QoS performance, we perform simulations using a custom implementation in the Go language. The evaluation considers three key QoS metrics: expected download failure volume ($E[V_F]$), deadline miss ratio (P_{miss}), and QoS satisfaction probability (P_{QoS}), as defined in (14)–(21). We compare four schemes: MLSR, MLMR with dual-link and triple-link configurations, and MO based on the model of Sou and Peng [6], which integrates cellular and WiFi paths using MPTCP.

All schemes are evaluated under a baseline configuration summarized in Table II. In the MO scheme, the average bandwidths for cellular and WiFi paths are set to 40 Mbps and 60 Mbps, respectively. For MLMR-dual-link, the primary and secondary links are configured with 40 Mbps and 60 Mbps. In the MLMR-triple-link scheme, the three links are assigned 40 Mbps, 50 Mbps, and 60 Mbps, respectively. The average connection durations across all three WiFi links ($E[T_i]$) are assumed equal (i.e., $E[T_c] = E[T_1] = E[T_2] = E[T_3]$). For the expected file size $E[F]$, we model F using a Pareto distribution with a mean of 1 GB. Its scale and shape parameters are set to $x_m = 800$ MB and $\alpha = 5$, respectively, ensuring that the simulated file size never falls below 800 MB while allowing variability around the mean. Finally, the simulation is executed for 100,000 iterations.

A. Effect of user session time, t_s

As shown in Fig. 4, both the MLMR-triple link and MO schemes achieve near-optimal QoS when the session time is



(a) Average Failure Volume. (b) Deadline Miss Ratio. (c) QoS Satisfaction.

Fig. 5: The output metrics against the expected ratio between $E[T_c]$ and $E[T_0]$.

sufficiently long. The triple-link scheme usually outperforms the MO scheme in improving all metrics with a marginal improvement of approximately 3%. In Figs. 4a and 4b, the average download failure volume ($E[V_F]$) and deadline miss ratio (P_{miss}) for these two schemes drop sharply, approaching zero when $t_s \geq 320$ seconds, highlighting their ability to complete transfers before the deadline. In contrast, the MLSR and MLMR-dual link schemes perform worse due to limited bandwidth diversity. Their $E[V_F]$ and P_{miss} values remain high under shorter deadlines. Fig. 4c confirms that only MO and triple-link consistently achieve high QoS satisfaction (P_{QoS}), with both reaching near 100% for longer sessions. In general, these two schemes outperform the others by roughly 90% in reducing $E[V_F]$ and 85% in minimizing P_{miss}.

B. Effect of $E[T_c]$ to $E[T_0]$

As shown in Fig. 5, the performance of all schemes improves as the duration of the WiFi connection increases. When $E[T_c] \geq 2E[T_0]$, the MLMR schemes, especially the triple-link configuration, begin to consistently outperform the MO scheme across all metrics. In particular, the triple-link scheme achieves superior utilization of the available bandwidth, resulting in lower average failure volume, fewer deadline miss ratio, and higher QoS satisfaction. For example, under $E[T_c] > E[T_0]$, its average deadline miss ratio is 1.52%, significantly outperforming the MO scheme's 4.71%, reflecting a 68% lower miss ratio. This highlights the effectiveness of coordinated multi-link usage under favorable connection durations.

V. Conclusion

This paper proposed novel analytical models to characterize WiFi link visit behavior and evaluate QoS performance under various MLO schemes in WiFi 7 networks. Their validity was confirmed through simulations, showing close alignment between theoretical and empirical results. Numerical evaluations demonstrated that multi-link configurations—especially the MLMR-triple-band scheme can outperform the existing MO scheme, particularly in reducing download failures and deadline misses. The proposed framework offers a scalable foundation for analyzing next-generation wireless access strategies under heterogeneous and time-varying conditions. As future work, we aim to develop adaptive MLO selection policies, potentially leveraging reinforcement learning or multi-armed bandits to optimize QoS in real-time.

References

[1] B. Crow, I. Widjaja, J. Kim, and P. Sakai, "Ieee 802.11 wireless local area networks," *IEEE Communications Magazine*, vol. 35, no. 9, pp. 116–126, 1997.

[2] K. Srisomboon, K. Wasayangkool, and W. Lee, "Trilateral smart switching algorithm for improving smart meters efficiency in advanced metering infrastructure (ami) network," *IEEE Access*, vol. 12, pp. 194 973–194 988, 2024.

[3] A. Ford, C. Raiciu, M. Handley, and O. Bonaventure, "Tcp extensions for multipath operation with multiple addresses," Tech. Rep., 2013.

[4] N. Bhooanusas and S.-I. Sou, "Performance modeling of multipath mobile data offloading in cellular/wifi networks with bandwidth uncertainty," *Computer Networks*, vol. 197, p. 108351, 2021.

[5] S. M. Ross, *Introduction to Probability Models*, 11th ed. Boston, MA, USA: Academic Press, 2014.

[6] S.-I. Sou and Y.-T. Peng, "Performance modeling for multipath mobile data offloading in cellular/wi-fi networks," *IEEE Transactions on Communications*, vol. 65, no. 9, pp. 3863–3875, 2017.

[7] X. Zhuo, W. Gao, G. Cao, and S. Hua, "An incentive framework for cellular traffic offloading," *IEEE Transactions on Mobile Computing*, vol. 13, no. 3, pp. 541–555, 2014.

[8] K. B. Pisupati and V. Ramaiyan, "Enhancements to wi-fi link models in ns-3 for indoor wlan s," in *2024 National Conference on Communications (NCC)*, 2024, pp. 1–6.

[9] IEEE, *IEEE Standard for Information Technology—Telecommunications and information exchange between systems Local and metropolitan area networks—Specific requirements Part 11: Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications*, IEEE Std. 802.11ax-2019, 2019.

[10] MediaTek Inc., "Wi-fi 7 multi-link operation (mlo)," https://728015.fs1.hubspotusercontent-na1.net/hubfs/728015/Wi-Fi-7-MLO-White-Paper-WF7MLOWP0622.pdf, 2022, white paper. Retrieved August 18, 2025.

[11] N. Korolev, I. Levitsky, and E. Khorov, "Analytical model of multi-link operation in saturated heterogeneous wi-fi 7 networks," *IEEE Wireless Communications Letters*, vol. 11, no. 12, pp. 2546–2549, 2022.

[12] L. Zhang, H. Yin, S. Roy, L. Cao, X. Gao, and V. Sathya, "Ieee 802.11be network throughput optimization with multilink operation and ap controller," *IEEE Internet of Things Journal*, vol. 11, no. 13, pp. 23 850–23 861, 2024.

[13] G. Bianchi, "Performance analysis of the ieee 802.11 distributed coordination function," *IEEE Journal on Selected Areas in Communications*, vol. 18, no. 3, pp. 535–547, 2000.

[14] S. Lian, J. Tong, and L. Fu, "Dynamic channel allocation via bandit learning for wifi 7 networks with multi-link operation," in *2025 IEEE Wireless Communications and Networking Conference (WCNC)*, 2025, pp. 1–6.