

Efficient Service Differentiation and Energy Management in Hybrid WiFi/LiFi Networks

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Abstract—In this paper, we propose a predict-and-optimize algorithm for hybrid WiFi/LiFi networks to enable service differentiation while maximizing energy efficiency (EE). The framework dynamically predicts the appropriate network slice for each user based on historical key performance indicators (KPIs), using a deep learning model trained with the resilient backpropagation algorithm. Subsequently, the algorithm optimizes EE as a function of precoding vectors for the predicted slices using sequential convex approximation and the inner approximation method. Novel approximations are introduced to convert non-convex objectives and constraints into convex forms, enabling an iterative algorithm to compute sub-optimal solutions. The EE formulation complies with end-to-end latency requirements and addresses hybrid-specific constraints, such as LED input signal limitations, data rate thresholds, and power budgets. Slice-specific quality of service (QoS) demands are incorporated by modeling enhanced mobile broadband (eMBB) with infinite blocklength capacity and using finite blocklength approximations for ultra-reliable low-latency communication (URLLC) and massive machine-type communications (mMTC), ensuring realistic reliability and latency treatment. Simulation results demonstrate that the proposed algorithm achieves up to 37% EE improvement over Zero-Forcing (ZF) precoding. It converges within 10–20 iterations and exhibits robust scalability with increasing numbers of access points, validating its effectiveness for next-generation heterogeneous wireless networks.

Index Terms—Energy Efficiency, Hybrid WiFi/LiFi, mATRIC, Network Slicing, Precoding, Service Differentiation.

I. INTRODUCTION AND MOTIVATION

The exponential growth in mobile data traffic and the diverse requirements of emerging applications necessitate innovative solutions in wireless communication systems. The advent of 5G technology and subsequent generations has highlighted the potential of network slicing. Network slicing allows for the differentiation of services by segmenting the network into distinct slices, each adapted to specific application needs [1]. This capability supports the heterogeneous needs of enhanced mobile broadband (eMBB), ultra-reliable low-latency communication (URLLC), and massive machine-type communications (mMTC), while striving to balance performance with

energy efficiency (EE). Despite its advantages in managing diverse service requirements, network slicing poses challenges, particularly related to energy consumption and operational costs, raising concerns about sustainability [2]. As network operators aim to deliver a broad range of services, integrating energy-efficient strategies becomes essential.

Open Radio Access Network (O-RAN) is an initiative to develop an open, disaggregated RAN architecture that promotes interoperability and flexibility by standardizing interfaces and components. This approach allows for greater innovation and cost-efficiency, enabling seamless integration of different radio technologies into a cohesive network ecosystem. O-RAN will unify various radio technologies, including non-3GPP technologies, Wi-Fi, and LiFi, to satisfy the diverse requirements of future wireless networks and create a more integrated and versatile communication infrastructure [3]. For control and optimization of RAN functions across multi-access technologies, including all wired and wireless technologies, the realizing enabling architectures and solutions for open networks (REASON) project plays a crucial role. REASON is dedicated to advancing the O-RAN initiative by developing a multi-access technology real-time intelligent controller (mATRIC), an innovative framework designed to manage and optimize a diverse array of access technologies [4]. It acts as a central component, receiving policy directives from the universal non-real time RAN intelligent controller (non-RT RIC) and executing real-time control and optimization of multi-access technologies. By utilizing collected data, mATRIC ensures dynamic network performance and adaptability, and supports various xApps. Here, xApps are microservice-based applications that are executed on the mATRIC to enhance network functionality and efficiency in real-time.

In O-RAN, non-3GPP access networks, like WiFi and LiFi, can be integrated using non-3GPP interworking functions. Both WiFi and LiFi networks can connect through the same interworking function, but each network uses its own separate IP subnetwork. To fully capitalize on the benefits of mATRIC for hybrid WiFi/LiFi networks, it is crucial to extend network slicing to accommodate these hybrid technologies and applications within the RAN ecosystem [5]. Consequently, supporting network slicing for each technology is essential. For WiFi and LiFi networks, slicing can be effectively applied to address their unique requirements, allowing for the creation of tailored virtual slices that optimize performance and resource allocation. This approach ensures that each network can meet specific needs, such as high-density WiFi environments or high-speed LiFi communications, enhancing overall efficiency and service quality [6]–[8]. By applying network slicing to a hybrid setup, it is possible to optimize

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This work was presented in part as an extended abstract at the 52nd Wireless World Research Forum (WWRF52), held at King's College London, UK, from September 10–12, 2024.

This work was supported in part by the Project REASON, a UK Government funded Project through the Future Open Networks Research Challenge (FONRC) sponsored by the Department of Science Innovation and Technology (DSIT), and in part by the Engineering and Physical Sciences Research Council (EPSRC) through the Platform for Driving Ultimate Connectivity (TITAN), EP/X04047X/1 and EP/Y037243/1.

the use of both WiFi and LiFi resources in a coordinated manner through mATRIC. mATRIC can dynamically allocate resources among different access technologies and network slices, ensuring optimal performance for eMBB, URLLC, and mMTC applications.

To effectively support the diverse service requirements of eMBB, URLLC, mMTC in a hybrid WiFi/LiFi network, it is crucial to consider the specific transmission needs of each service type. Each of these services has distinct performance and reliability requirements that impact the design of the network and the optimization strategies employed. For URLLC, which demands extremely low latency and high reliability, the transmission duration plays a critical role. Given that the end-to-end latency requirement for URLLC is approximately 1 millisecond [9], [10], a transmission duration of 0.05 milliseconds [11], [12] is sufficient to meet this stringent requirement [13]. Finite block length transmission is crucial here due to the short block lengths involved, which affect error rates. Traditional Shannon capacity, applicable to longer block lengths, does not accurately reflect achievable rates for URLLC. Instead, the Polyanskiy bound [14] considering finite block lengths, provides a more accurate measure of achievable rates, which are lower than those predicted by Shannon capacity. This necessitates algorithms that handle finite block lengths effectively to ensure high reliability and meet URLLC's stringent performance requirements. For mMTC, which manages numerous devices with intermittent communication needs, finite block length transmission is particularly advantageous. While mMTC's latency requirements are less stringent than those of URLLC, short block lengths are still valuable due to the nature of mMTC's communication. This technology often involves transmitting short payloads, where ensuring reliability and efficiency is crucial. Finite block length transmission enables the system to handle these brief communication intervals effectively, maintaining reliable performance, thus aligning well with the demands of mMTC [15]. Dealing with the finite block length constraints for URLLC and mMTC, alongside traditional large block length transmission for eMBB, presents a complex challenge for resource allocation. This scenario introduces novel optimization problems that require advanced strategies for efficient resource management [16].

In hybrid WiFi/LiFi networks, most studies have contributed towards key issues such as EE [17], [18], load balancing [19], [20], handover [21], user association [22], [23], and access point selection [24]. However, a notable gap exists in integrating service differentiation with EE, an aspect that remains unexplored in hybrid WiFi/LiFi networks. Addressing this gap, our work focuses on developing strategies that not only balance performance and energy consumption but also meet diverse service requirements of different applications, thereby fully exploiting the potential of hybrid networks. Our major contribution is summarized as follows:

- A novel predict-and-optimize algorithm is proposed for hybrid WiFi/LiFi networks to enable service differentiation while maximizing EE. In the first stage, the slice type for each user is dynamically predicted using a deep learning model trained on monitored KPIs. In the second stage, the EE of the hybrid network is maximized

as a function of the precoding vectors corresponding to the predicted slice types. Slice-specific models are incorporated by modeling eMBB traffic using infinite blocklength capacity and URLLC/mMTC using finite blocklength transmission. The formulation also accounts for latency, data rate, power budget, and LiFi input signal constraints.

- The proposed algorithm's worst-case computational complexity is computed using Big O notation and is observed to be low, ensuring both practical efficiency and scalability. This makes the algorithm suitable for real-world deployment in hybrid WiFi/LiFi networks, as both the neural network prediction and EE optimization phases handle complex tasks with manageable computational demands.
- Numerical results are presented, demonstrating the fast convergence of the proposed algorithm and its effectiveness in optimizing transmit precoding vectors for hybrid WiFi/LiFi networks with RAN slicing support. This results in enhanced EE while maintaining effective service differentiation.
- In our study, we compared the performance of our proposed optimization algorithm for EE maximization as a function of precoding vectors in hybrid networks with conventional precoding methods, such as Zero-Forcing (ZF) and Maximum Ratio Transmission (MRT). The results indicate that our algorithm significantly outperforms these traditional methods in terms of EE while effectively ensuring service differentiation. Additionally, we assessed the performance of a fully hybrid LiFi/WiFi system versus a WiFi-only system. The hybrid system, which makes use of both WiFi and LiFi transmitters, demonstrates superior EE compared to the WiFi-only system. This highlights the benefits of integrating LiFi with WiFi, not only in optimizing resource use but also in enhancing service differentiation and overall network performance.

The remainder of the paper is organized as follows: Section II presents the system model, including the hybrid network architecture, slice structure and network intelligence, channel models, energy efficiency formulation, and latency model. Section III formulates the problem and details the proposed solution. Section IV provides numerical simulations and relevant discussions. Section V outlines potential real-world applications of the proposed approach. Finally, Section VI concludes the paper and highlights directions for future research. The definitions of various symbols used throughout the paper are summarized in Table I.

II. SYSTEM MODEL

A. Hybrid Network Architecture

We consider a hybrid WiFi/LiFi system, as illustrated in Fig. 1, which comprises multi LED LiFi transmitter and a multi-antenna WiFi transmitter that serves K users, with each user equipped with both a photodiode and an antenna. Each user is indexed by k such that $k \in \{1, 2, \dots, K\}$. Moreover, the system model considers the size of the room, which can

TABLE I
LIST OF SYMBOLS AND THEIR DEFINITIONS

Symbol	Definition
K	Total number of users in the system.
M	Number of antennas at the WiFi transmitter.
L	Number of LEDs at the LiFi transmitter.
s	Type of service, where $s \in \{eMBB, URLLC, mMTC\}$.
$\mathbf{h}_{k,s}^{\text{WiFi}}$	Channel link between the WiFi transmitter and the k^{th} user in slice s .
$\mathbf{h}_{k,s}^{\text{LiFi}}$	Channel link between the LiFi transmitter and the k^{th} user in slice s .
$\mathbf{f}_{k,s}^{\text{WiFi}}$	WiFi precoder for the k^{th} user in slice s .
$\mathbf{f}_{k,s}^{\text{LiFi}}$	LiFi precoder for the k^{th} user in slice s .
$(\sigma_{k,s}^{\text{WiFi}})^2$	Variance of AWGN for the k^{th} user in WiFi slice s .
$(\sigma_{k,s}^{\text{LiFi}})^2$	Variance of AWGN for the k^{th} user in LiFi slice s .
$\gamma_{k,s}^{\text{WiFi}}$	SINR of the k^{th} user in WiFi slice s .
$\gamma_{k,s}^{\text{LiFi}}$	SINR of the k^{th} user in LiFi slice s .
$R_{k,s}^{\text{WiFi}}$	Achievable rate of the k^{th} user in WiFi slice s .
$R_{k,s}^{\text{LiFi}}$	Achievable rate of the k^{th} user in LiFi slice s .
$S_{k,s}^{\text{WiFi}}$	Shannon term of the k^{th} user in WiFi slice s .
$V_{k,s}^{\text{WiFi}}$	Channel dispersion term of the k^{th} user in WiFi slice s .
$S_{k,s}^{\text{LiFi}}$	Shannon term of the k^{th} user in LiFi slice s .
$V_{k,s}^{\text{LiFi}}$	Channel dispersion term of the k^{th} user in LiFi slice s .
P_{WiFi}	Power consumption of the WiFi transmit signal.
P_{LiFi}	Power consumption of the LiFi transmit signal.
$T_{k,s}$	Total latency for the transmission to the k^{th} user in slice s .

be expressed as $L \times W \times H$ cubic meters, where L is the length, W is the width, and H is the height. For this model, the room dimensions are 10 meters in length, 10 meters in width, and 5 meters in height. The WiFi transmitter is placed at the center of the room at coordinates $(W/2, L/2)$. The ceiling of the room is divided into a grid pattern, with I intervals along both the X and Y axes, resulting in a total of $I \times I$ LED positions. Each LED is positioned at a height of $H - 1$ meters above the floor, ensuring a uniform distribution throughout the room. The specific positions of the LEDs are determined by dividing the room width and length into equal segments and placing the LEDs at these intervals. We adopt a cell-free VLC architecture, where all distributed LEDs are centrally coordinated through a controller that manages joint transmission and precoding. These LEDs simultaneously serve all users without fixed cell boundaries or static user-to-LED associations [25]. Additionally, the K users are randomly distributed throughout the room, with their locations modeled using a binomial point process (BPP). Each user is exclusively associated with a single network slice $s \in \{eMBB, URLLC, mMTC\}$, determined during the initial slice prediction phase. This slice assignment remains fixed throughout the optimization process and is used to compute slice-specific transmission parameters. Users do not simultaneously belong to or transmit data across multiple slices.

B. Slice Structure and Network Intelligence

This subsection describes the slice structure adopted for the hybrid WiFi/LiFi network, focusing on service differentiation and intelligent slice allocation. Specifically, we consider three

slice types: $s \in \{eMBB, URLLC, mMTC\}$, each customized to meet distinct application requirements [6], [7]. To improve resource utilization, we adopt a soft isolation slicing model [26], [27], wherein all slices share the same physical-layer resources (e.g., bandwidth, LEDs, antennas). Rather than static partitioning, slice-aware centralized precoding is used to mitigate both intra-slice and inter-slice interference, ensuring service differentiation and QoS adherence without hard isolation constraints. mATRIC is tasked with the efficient allocation of network slices and the maximization of EE within a hybrid network environment. Slice selection is driven by KPIs collected by mATRIC from various network nodes such as latency, reliability, supported technologies, use case category, and temporal information from the network infrastructure. Machine learning model is trained on historical KPI data by the universal non-RT RIC, which can be employed in real time through mATRIC to automate slice selection, ensuring that the network meets the diverse demands of applications and users effectively.

C. Channel Modeling for Hybrid WiFi/LiFi Links

For the WiFi channel, the model for the channel from the WiFi transmitter to the k^{th} user at slice s incorporates both channel fading and path loss. It is given by [24]:

$$\mathbf{h}_{k,s}^{\text{WiFi}} = \left[\sqrt{\frac{\delta}{1+\delta}} e^{j\frac{\pi}{4}} + \sqrt{\frac{1}{1+\delta}} \mathbf{g}_{k,s} \right] 10^{\frac{-PL[\text{dB}]}{20}}, \quad (1)$$

where $\mathbf{g}_{k,s} \in \mathbb{C}^M$, and M is the number of antennas at the WiFi transmitter. The Ricean factor δ is set to 1 for distances up to the breakpoint distance d_{BP} , and it drops to 0 for distances beyond d_{BP} . Additionally, the path loss $PL[\text{dB}]$ is described as:

$$PL[\text{dB}] = \begin{cases} L(d_{k,s}) + \Omega_{\text{in}}, & d_{k,s} \leq d_{BP}, \\ L(d_{k,s}) + 35 \log_{10}\left(\frac{d_{k,s}}{d_{BP}}\right) + \Omega_{\text{out}}, & d_{k,s} > d_{BP}, \end{cases}, \quad (2)$$

where the free space path loss for WiFi is expressed as

$$L(d_{k,s}) = 20 \log_{10}(d_{k,s}) + 20 \log_{10}(f_c) - 147.5, \quad (3)$$

with f_c as the central carrier frequency. The shadow fading is modeled as Gaussian random variables, where $\Omega_{\text{in}} \sim \mathcal{N}(0, \sigma_{\text{in}}^2)$ for distances within d_{BP} , and $\Omega_{\text{out}} \sim \mathcal{N}(0, \sigma_{\text{out}}^2)$ for distances beyond d_{BP} . For the LiFi channel in our analysis, we extend our modeling approach to include the transmission from a multi-LED LiFi transmitter to the k^{th} user at slice s . For LiFi channels, only Line-of-Sight (LoS) links are taken into account, as they carry the majority of the transmitted power, while the power contribution from non-Line-of-Sight (NLoS) links is relatively minimal [28]. The locations of the l^{th} LED and the k^{th} user in a three-dimensional Cartesian coordinate system are represented by $(x_l^{\text{LED}}, y_l^{\text{LED}}, z_l^{\text{LED}})$ and $(x_k^{\text{user}}, y_k^{\text{user}}, z_k^{\text{user}})$, respectively. The distance between the l^{th} LED and the k^{th} user, considering only the LoS path, is given by

$$d_{l,k} = \sqrt{(x_l^{\text{LED}} - x_k^{\text{user}})^2 + (y_l^{\text{LED}} - y_k^{\text{user}})^2 + (z_l^{\text{LED}} - z_k^{\text{user}})^2}. \quad (4)$$

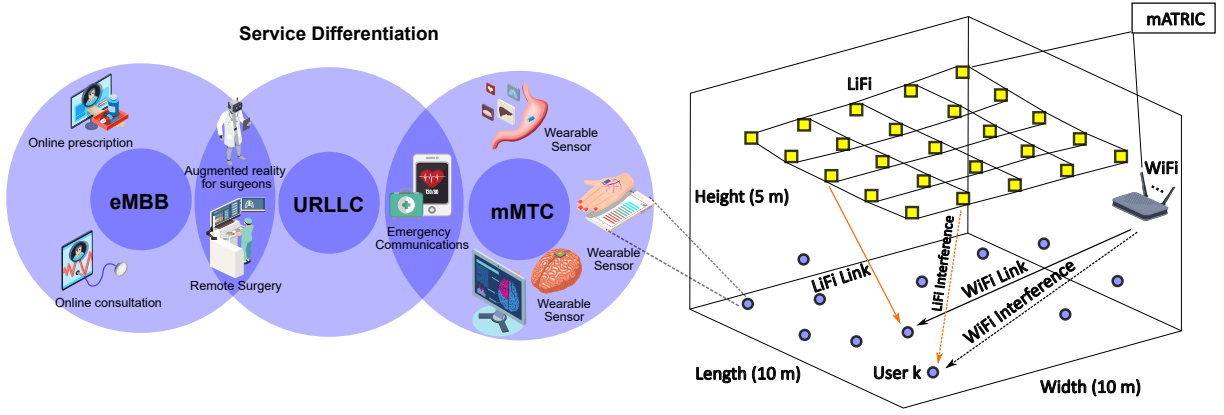


Fig. 1. Illustration of System Model

It is assumed that the transceivers' normal vectors are aligned perpendicularly to the ground plane. Consequently, the angles of irradiance $\Theta_{l,k}$ and incidence $\phi_{l,k}$ for each Line-of-Sight (LoS) component of the channel gain are defined as follows [29]:

$$\Theta_{l,k} = \phi_{l,k} = \arccos\left(\frac{z_l^{\text{LED}} - z_k^{\text{user}}}{d_{l,k}}\right). \quad (5)$$

Now, the LoS channel gain between the l^{th} LED and the k^{th} user at slice s can be modeled through Lambertian radiant formulation as described below [30]:

$$h_{l,k,s} = \begin{cases} \frac{(m+1)A_D G_f R_D}{2\pi d_{l,k}^2} \cos^m(\Theta_{l,k}) \cos(\phi_{l,k}) g(\phi_{l,k}), & 0 \leq \phi_{l,k} \leq \phi_{\text{FoV}}, \\ 0, & \text{otherwise.} \end{cases} \quad (6)$$

The Lambertian index m is determined by the transmitter's half-intensity radiation angle $\psi_{1/2}$ as $m = \frac{-1}{\log_2(\cos(\psi_{1/2}))}$. Variables A_D , G_f , and R_D represent the physical area of the detector, the gain of the optical filter, and the responsivity of the detector, respectively. ϕ_{FoV} signifies the field of view (FoV) of the detector. The optical concentrator gain $g(\phi_{l,k})$ is defined as

$$g(\phi_{l,k}) = \begin{cases} \frac{r^2}{\sin^2(\phi_{\text{FoV}})}, & \text{if } 0 \leq \phi_{l,k} \leq \phi_{\text{FoV}}, \\ 0, & \text{otherwise,} \end{cases} \quad (7)$$

where r represents the refractive index, typically ranging between 1 and 2 for visible light. We assume perfect channel state information (CSI) at the transmitter and quasi-static user positions during each optimization interval. These standard assumptions are widely used to ensure a tractable formulation and enable efficient algorithm design [17], [24]. While they may result in optimistic performance estimates, particularly under user mobility or CSI uncertainty, incorporating these practical considerations is left for future work.

D. Energy Efficiency Formulation for Hybrid Wi-Fi/Li-Fi Network

1) *Signal and Interference Model:* In Li-Fi, the detection of signals is based on counting the received photons, which necessitates that the visible light signals be real-valued and

non-negative. The transmitted signals for all users are represented by the vector $\mathbf{a}_s^{\text{LiFi}} = [a_{1,s}^{\text{LiFi}}, a_{2,s}^{\text{LiFi}}, \dots, a_{K,s}^{\text{LiFi}}]^T \in \mathbb{R}^{K \times 1}$, and $\mathbf{F}_s^{\text{LiFi}} = [\mathbf{f}_{1,s}^{\text{LiFi}}, \mathbf{f}_{2,s}^{\text{LiFi}}, \dots, \mathbf{f}_{K,s}^{\text{LiFi}}] \in \mathbb{R}^{L \times K}$ as the corresponding precoding matrix, with $\mathbf{f}_{k,s}^{\text{LiFi}}$ being the precoding vector for $a_{k,s}^{\text{LiFi}}$, which is defined as $\mathbf{f}_{k,s}^{\text{LiFi}} = [f_{1,k,s}^{\text{LiFi}}, f_{2,k,s}^{\text{LiFi}}, \dots, f_{L,k,s}^{\text{LiFi}}]^T \in \mathbb{R}_+^{L \times 1}$. Without loss of generality, these signals are normalized such that $\mathbb{E}\{a_{k,s}^{\text{LiFi}}\} = 0$ and $\mathbb{E}\{(a_{k,s}^{\text{LiFi}})^2\} = 1$. Hence, the real-valued input electric signal at the l^{th} LED for the slice s is obtained by summing all the weighted symbols for the K users, given by

$$x_{l,s}^{\text{LiFi}} = \sum_{k=1}^K f_{l,k,s}^{\text{LiFi}} a_{k,s}^{\text{LiFi}}. \quad (8)$$

However, $x_{l,s}^{\text{LiFi}}$ cannot be used directly as the input signal to the l^{th} LED at slice s because it can sometimes be negative. To ensure proper illumination, a DC bias $x_{\text{DC},l}^s$ must be added to $x_{l,s}^{\text{LiFi}}$ to generate a non-negative drive current $I_{l,s}$ for the LED. Additionally, this drive current must be limited to a maximum threshold $I_{\text{max},s}$ to guarantee the normal operation of the LEDs. This can be expressed as

$$0 \leq I_{l,s} = x_{l,s}^{\text{LiFi}} + x_{\text{DC},l}^s \leq I_{\text{max},s}, \quad \forall l. \quad (9)$$

To ensure Eq. (9), the following constraint should be satisfied [31]

$$\sum_{k=1}^K |f_{l,k,s}^{\text{LiFi}}| = \min(x_{\text{DC},l}^s, I_{\text{max},s} - x_{\text{DC},l}^s). \quad (10)$$

$\mathbf{f}_{k,s}^{\text{LiFi}} = [f_{1,k,s}^{\text{LiFi}}, f_{2,k,s}^{\text{LiFi}}, \dots, f_{L,k,s}^{\text{LiFi}}]^T \in \mathbb{R}_+^{L \times 1}$ represents the real-valued precoding vector for the k^{th} user from an L -LED Li-Fi transmitter, and $\mathbf{h}_{k,s}^{\text{LiFi}} = [h_{1,k,s}^{\text{LiFi}}, h_{2,k,s}^{\text{LiFi}}, \dots, h_{L,k,s}^{\text{LiFi}}]^T \in \mathbb{R}_+^{L \times 1}$ denote the channel gain vector for the k^{th} user from a multi LED Li-Fi transmitter. After eliminating the DC component, the received signal at the k^{th} user at the slice s can be expressed as

$$y_{k,s}^{\text{LiFi}} = \underbrace{(\mathbf{h}_{k,s}^{\text{LiFi}})^T \mathbf{f}_{k,s}^{\text{LiFi}} a_{k,s}^{\text{LiFi}}}_{\text{Desired signal}} + \underbrace{\sum_{j \neq k} (\mathbf{h}_{k,s}^{\text{LiFi}})^T \mathbf{f}_{j,s}^{\text{LiFi}} a_{j,s}^{\text{LiFi}}}_{\text{Interference from other users}} + n_{k,s}^{\text{LiFi}}. \quad (11)$$

$n_{k,s}^{\text{LiFi}}$ represents the noise at the k^{th} user at slice s . This noise is modeled as additive white Gaussian noise (AWGN) with zero mean and variance $(\sigma_{k,s}^{\text{LiFi}})^2$. Specifically, the noise for each user satisfies the Gaussian distribution $n_{k,s}^{\text{LiFi}} \sim \mathcal{N}(0, (\sigma_{k,s}^{\text{LiFi}})^2)$. The variance $(\sigma_{k,s}^{\text{LiFi}})^2$ is given by $(\sigma_{k,s}^{\text{LiFi}})^2 = \mu_{k,s}^{\text{LiFi}} \cdot \text{BW}_{k,s}^{\text{LiFi}}$, where $\mu_{k,s}^{\text{LiFi}}$ is the power spectral density (PSD) of AWGN for LiFi, and $\text{BW}_{k,s}^{\text{LiFi}}$ is the bandwidth of the LiFi link.

Furthermore, we assume that the WiFi transmitter uses a standard block-level precoding with $\mathbf{a}_s^{\text{WiFi}} = [a_{1,s}^{\text{WiFi}}, a_{2,s}^{\text{WiFi}}, \dots, a_{K,s}^{\text{WiFi}}]^T \in \mathbb{C}^{K \times 1}$ being the symbol vector of all K users from the WiFi transmitter. The symbol vector is precoded by $\mathbf{F}_s^{\text{WiFi}} = [\mathbf{f}_{1,s}^{\text{WiFi}}, \mathbf{f}_{2,s}^{\text{WiFi}}, \dots, \mathbf{f}_{K,s}^{\text{WiFi}}] \in \mathbb{C}^{M \times K}$, with $\mathbf{f}_{k,s}^{\text{WiFi}} = [f_{1,k,s}^{\text{WiFi}}, f_{2,k,s}^{\text{WiFi}}, \dots, f_{M,k,s}^{\text{WiFi}}]^T \in \mathbb{C}^{M \times 1}$ being the WiFi precoder. Consequently, the transmitted signal can be written as

$$\mathbf{x}_s^{\text{WiFi}} = \mathbf{F}_s^{\text{WiFi}} \mathbf{a}_s^{\text{WiFi}} = \sum_{k=1}^K \mathbf{f}_{k,s}^{\text{WiFi}} a_{k,s}^{\text{WiFi}}. \quad (12)$$

Thus, the signal received from the WiFi transmitter by the k^{th} user at the slice s is given by

$$y_{k,s}^{\text{WiFi}} = \underbrace{(\mathbf{h}_{k,s}^{\text{WiFi}})^H \mathbf{f}_{k,s}^{\text{WiFi}} a_{k,s}^{\text{WiFi}}}_{\text{Desired signal}} + \underbrace{\sum_{j \neq k} (\mathbf{h}_{k,s}^{\text{WiFi}})^H \mathbf{f}_{j,s}^{\text{WiFi}} a_{j,s}^{\text{WiFi}}}_{\text{Interference from other users}} + n_{k,s}^{\text{WiFi}}, \quad (13)$$

where $n_{k,s}^{\text{WiFi}}$ denotes the noise at the k^{th} user at the slice s . The noise at each user satisfies complex Gaussian distribution $n_{k,s}^{\text{WiFi}} \sim \mathcal{CN}(0, (\sigma_{k,s}^{\text{WiFi}})^2)$. The variance $(\sigma_{k,s}^{\text{WiFi}})^2$ is given by $(\sigma_{k,s}^{\text{WiFi}})^2 = \mu_{k,s}^{\text{WiFi}} \cdot \text{BW}_{k,s}^{\text{WiFi}}$, where $\mu_{k,s}^{\text{WiFi}}$ is the power spectral density (PSD) of AWGN for WiFi, and $\text{BW}_{k,s}^{\text{WiFi}}$ is the bandwidth of the WiFi link. Each WiFi signal for the k^{th} user follows a complex normal distribution with mean 0 and variance 1, denoted as $a_{k,s}^{\text{WiFi}} \sim \mathcal{CN}(0, 1)$. In the considered hybrid network, each user k is exclusively assigned to a slice $s \in \{\text{eMBB}, \text{URLLC}, \text{mMTC}\}$ during the initial prediction phase. All slices share the same physical-layer resources under a soft isolation model [26], [27], allowing for both intra- and inter-slice interference. Accordingly, the interference terms in equations (11) and (13) account for signals from users within the same slice as well as from other slices. The notation $y_{k,s}$, along with the SINR and rate expressions, refers to user k 's assigned slice s , which remains fixed and does not imply multi-slice access.

2) *SINR and Rate Expressions*: Based on the previously established signal models, the SINRs of user k at the slice s for WiFi and LiFi are represented as

$$\gamma_{k,s}^{\text{WiFi}} = \frac{X_{k,s}^{\text{WiFi}}}{Y_{k,s}^{\text{WiFi}}} = \frac{\left| (\mathbf{h}_{k,s}^{\text{WiFi}})^H \mathbf{f}_{k,s}^{\text{WiFi}} \right|^2}{\sum_{j \neq k} \left| (\mathbf{h}_{k,s}^{\text{WiFi}})^H \mathbf{f}_{j,s}^{\text{WiFi}} \right|^2 + (\sigma_{k,s}^{\text{WiFi}})^2}, \quad (14)$$

$$\gamma_{k,s}^{\text{LiFi}} = \frac{X_{k,s}^{\text{LiFi}}}{Y_{k,s}^{\text{LiFi}}} = \frac{\left| (\mathbf{h}_{k,s}^{\text{LiFi}})^T \mathbf{f}_{k,s}^{\text{LiFi}} \right|^2}{\sum_{j \neq k} \left| (\mathbf{h}_{k,s}^{\text{LiFi}})^T \mathbf{f}_{j,s}^{\text{LiFi}} \right|^2 + (\sigma_{k,s}^{\text{LiFi}})^2}. \quad (15)$$

For computing the achievable rates of LiFi links, the visible light signals must be real-valued and non-negative, making the classic Shannon formula with Gaussian input unsuitable. Since the channel capacity of LiFi is not available in closed form, we use some tight bounds to approximate the data rates. In this paper, we consider a lower bound of the achievable rate, given by [32]

$$R_{k,s}^{\text{LiFi}} = \underbrace{\frac{1}{2} \text{BW}_{k,s}^{\text{LiFi}} \ln \left(1 + \frac{e}{2\pi} \gamma_{k,s}^{\text{LiFi}} \right)}_{S_{k,s}^{\text{LiFi}}} \text{ nats/sec}, \quad (16)$$

while for WiFi, the achievable rate of user k at the slice s is

$$R_{k,s}^{\text{WiFi}} = \underbrace{\text{BW}_{k,s}^{\text{WiFi}} \ln (1 + \gamma_{k,s}^{\text{WiFi}})}_{S_{k,s}^{\text{WiFi}}} \text{ nats/sec}. \quad (17)$$

In our analysis, we consider three types of slices: $s \in \{\text{eMBB}, \text{URLLC}, \text{mMTC}\}$. The equations above are for $s \in \text{eMBB}$ applications, where longer block lengths are necessary to send data to meet high capacity demands. Conversely, $s \in \text{URLLC}$ requires very low latency, which can be achieved through shorter block-length data transmission to minimize delay. For $s \in \text{mMTC}$, which requires low latency and lower payload, short block-length data transmissions are also preferred. Shannon capacity is not applicable for short block-length data transmission due to the channel dispersion that arises [16]. Therefore, for the slice type of $s \in \{\text{URLLC}, \text{mMTC}\}$, which uses short block-length for data transmission, the achievable rate of user k at the slice s using the LiFi system $R_{k,s}^{\text{LiFi}}$ can be presented as

$$R_{k,s}^{\text{LiFi}} = \frac{1}{2} \text{BW}_{k,s}^{\text{LiFi}} \left\{ \underbrace{\ln \left(1 + \frac{e}{2\pi} \gamma_{k,s}^{\text{LiFi}} \right)}_{S_{k,s}^{\text{LiFi}}} - \underbrace{Q^{-1}(\epsilon) \sqrt{\frac{0.5 D_{k,s}^{\text{LiFi}}}{L_k}}}_{V_{k,s}^{\text{LiFi}}} \right\} \text{ nats/sec}. \quad (18)$$

where, $D_{k,s}^{\text{LiFi}} = 1 - \frac{1}{\left(1 + \frac{e}{2\pi} \gamma_{k,s}^{\text{LiFi}}\right)^2}$ is the channel dispersion while $L_k = \text{BW}_{k,s}^{\text{LiFi}} \times T_{k,s}^t$ indicates the associated transmit block-length. The scaling factor of 0.5 is applied to the achievable rate and channel dispersion $D_{k,s}^{\text{LiFi}}$ due to the utilization of Hermitian symmetry [33]. $S_{k,s}^{\text{LiFi}}$ represents the shanon term, while the $V_{k,s}^{\text{LiFi}}$ denotes the channel dispersion term. $Q^{-1}(\cdot)$ is the inverse function, with $Q^{-1}(x) = \int_x^\infty \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{t^2}{2}\right) dt$, and ϵ is the decoding error probability. Similarly, the achievable rate of user k at the slice s using the WiFi system $R_{k,s}^{\text{WiFi}}$ can be given as

$$R_{k,s}^{\text{WiFi}} = \text{BW}_{k,s}^{\text{WiFi}} \left\{ \underbrace{\ln (1 + \gamma_{k,s}^{\text{WiFi}})}_{S_{k,s}^{\text{WiFi}}} - \underbrace{Q^{-1}(\epsilon) \sqrt{\frac{D_{k,s}^{\text{WiFi}}}{L_k}}}_{V_{k,s}^{\text{WiFi}}} \right\} \text{ nats/sec}. \quad (19)$$

where, $D_{k,s}^{\text{WiFi}} = 1 - \frac{1}{(1+\gamma_{k,s}^{\text{WiFi}})^2}$ is the channel dispersion while $L_k = BW_{k,s}^{\text{WiFi}} \times T_{k,s}^t$, indicates the associated transmit blocklength.

3) *Power Consumption Model*: To evaluate EE, it is essential to characterize the power consumption of both WiFi and LiFi systems based on their signal transmission models. In LiFi, the total power consumption can be modeled as

$$P_{\text{LiFi}} = P_{\text{DC}} + P_{\text{AC}}, \quad (20)$$

where P_{DC} and P_{AC} denote the power of DC and AC current, respectively. P_{DC} includes $P_{\text{DC}}^{\text{LED}}$ for the illumination provided by the LEDs and $P_{\text{DC}}^{\text{circuit}}$ for the other circuit components. While $P_{\text{DC}}^{\text{circuit}}$ remains constant, the power used by the LEDs can be adjusted based on the dimming requirements. However, when the illumination level remains constant, $P_{\text{DC}}^{\text{LED}} = \sum_{l=1}^L V_F \cdot x_{\text{DC},l}^s$ can be considered fixed, where V_F is the forward voltage of LEDs. Therefore, $P_{\text{DC}} = P_{\text{DC}}^{\text{LED}} + P_{\text{DC}}^{\text{circuit}}$ has a fixed value based on dimming requirements. The AC currents are derived directly from the output current/voltage of the precoders in LED drivers, and thus can be computed as follows [31]

$$P_{\text{AC}} = \frac{1}{\eta_{\text{LiFi}}} \sum_{k=1}^K \left\| \mathbf{f}_{k,s}^{\text{LiFi}} \right\|^2, \quad (21)$$

where η_{LiFi} signifies the power amplifier efficiency of the LiFi transmitter. In this paper, we only consider the AC power consumption for wireless signal transmission. That is, $P_{\text{LiFi}} = P_{\text{AC}}$. For WiFi, the total power consumption can be computed as

$$P_{\text{WiFi}} = \frac{1}{\eta_{\text{WiFi}}} \sum_{k=1}^K \left\| \mathbf{f}_{k,s}^{\text{WiFi}} \right\|^2 + P_c^{\text{WiFi}}. \quad (22)$$

η_{WiFi} is the power amplifier efficiency of the WiFi transmitter. P_c^{WiFi} is the total circuit power at the WiFi. Similarly, for WiFi we consider only the power consumption for wireless signal transmission, that is $P_{\text{WiFi}} = \frac{1}{\eta_{\text{WiFi}}} \sum_{k=1}^K \left\| \mathbf{f}_{k,s}^{\text{WiFi}} \right\|^2$.

4) *EE Expression for Hybrid WiFi/LiFi Network*: After establishing the rate and power consumption models, we now present the EE expression for the hybrid WiFi/LiFi network. In this work, we aim to maximize the EE of the hybrid WiFi/LiFi transmitter while considering different slice types in order to support different applications. EE is defined as the ratio of the sum-rate of the system to the total power consumption [34] as follows:

$$\text{EE}^{\text{Hybrid}} = \frac{\sum_{k=1}^K R_{k,s}^{\text{WiFi}} + \sum_{k=1}^K R_{k,s}^{\text{LiFi}}}{P_{\text{WiFi}} + P_{\text{LiFi}}}. \quad (23)$$

Although the objective function adopts a sum-rate-based EE formulation, slice-aware service differentiation is incorporated via rate constraints, latency constraints, and QoS-aware user classification. Unlike weighted sum utilities, which require heuristic weight tuning and SLA-driven prioritization, our approach guarantees service compliance through hard constraints. This preserves fairness while ensuring tractable optimization under the SCA framework.

E. Latency Modeling

The total latency $T_{k,s}$ for transmission to the k^{th} user at the slice s includes several components: the queue waiting time $T_{k,s}^w$, the transmission time $T_{k,s}^t$, the channel access delay $T_{k,s}^a$, the backhaul delay $T_{k,s}^b$, the packet reception delay $T_{k,s}^r$, and the processing delay $T_{k,s}^p$. These components together define the total latency, given by [35]

$$T_{k,s} = T_{k,s}^w + T_{k,s}^t + T_{k,s}^a + T_{k,s}^b + T_{k,s}^r + T_{k,s}^p. \quad (24)$$

Based on the described hybrid WiFi/LiFi architecture, channel models, and slice-specific service requirements, we now proceed to formulate the EE optimization problem. This formulation accounts for the distinct transmission requirements of each slice (eMBB, URLLC, and mMTC), along with constraints such as power budgets, data rate requirements, latency, and LiFi input signal limitations. These elements are jointly considered in the slice-aware precoding framework detailed in the next section.

III. PROBLEM FORMULATION AND ITS SOLUTION

To provide a high-level overview of the proposed two-stage methodology, Fig. 2 illustrates the workflow of our predict-and-optimize algorithm. This includes the initial slice prediction based on KPI monitoring and the subsequent energy-efficient resource allocation phase via slice-aware precoding. The main objective is to maximize the EE at the hybrid WiFi/LiFi transmitter for any slice type s predicted for the users in stage 1 in order to support different applications. In this stage 2, the EE of the system is maximized through the optimization of the transmit precoding under the required system constraints. The Hybrid system constraints include the constraint on LEDs input signals for LiFi, end-to-end latency constraint, data rate constraint, and power budget constraint for the Hybrid system. Hence, the EE optimization problem is formulated as

$$\text{P1: } \max_{\mathbf{f}^{\text{WiFi}}, \mathbf{f}^{\text{LiFi}}} \text{EE}^{\text{Hybrid}} = \frac{\sum_{k=1}^K R_{k,s}^{\text{WiFi}} + \sum_{k=1}^K R_{k,s}^{\text{LiFi}}}{P_{\text{WiFi}} + P_{\text{LiFi}}} \quad (25)$$

Subject to:

$$\begin{aligned} \text{C1: } & R_{k,s}^{\text{WiFi}} + R_{k,s}^{\text{LiFi}} \geq R_{k,s}^{\min}, \quad \forall k, \\ \text{C2: } & P_{\text{WiFi}} + P_{\text{LiFi}} \leq P_{\text{max}}^{\text{Hybrid}}, \\ \text{C3: } & \sum_{k=1}^K |f_{l,k,s}^{\text{LiFi}}| \leq \min(x_{\text{DC},l}^s, I_{\text{max},s} - x_{\text{DC},l}^s), \quad \forall l, \\ \text{C4: } & T_{k,s} \leq T_{k,s}^{\min}, \quad \forall k. \end{aligned} \quad (26)$$

The optimization problem P1 is non-convex, making it challenging to achieve a globally optimal solution in practice. To address this, a sequential convex programming (SCP) strategy is employed to obtain a provably convergent iterative convex solution. By using SCP, the problem P1 is reformulated into a more manageable form by introducing a scalar variable: ψ^{Hybrid} , representing the total power consumption of the hybrid WiFi/LiFi system, and ϕ^{Hybrid} , representing the EE of

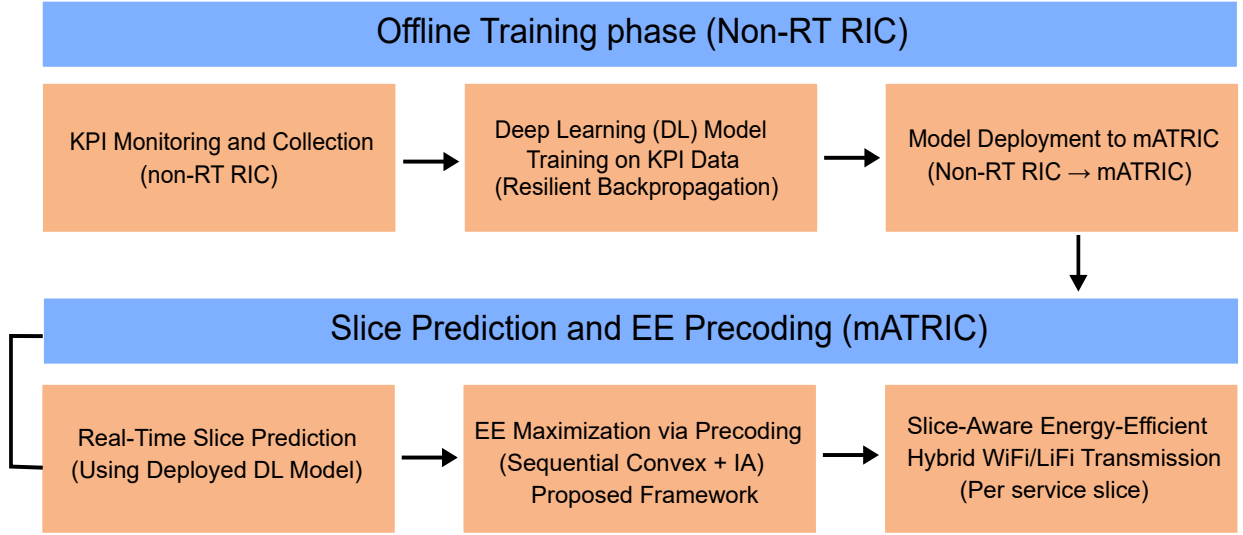


Fig. 2. Flowchart of the proposed Predict-and-Optimize Algorithm.

the hybrid system. The equivalent transformed optimization problem for P1 can then be expressed in P2 as follows:

$$\text{P2: } \max_{\mathbf{f}^{\text{WiFi}}, \mathbf{f}^{\text{LiFi}}, \phi^{\text{Hybrid}}, \psi^{\text{Hybrid}}} \phi^{\text{Hybrid}} \quad (27)$$

Subject to:

$$\begin{aligned} \text{C5: } & \text{EE}^{\text{Hybrid}} \geq \phi^{\text{Hybrid}}, \\ \text{C6: } & \sum_{k=1}^K R_{k,s}^{\text{WiFi}} + \sum_{k=1}^K R_{k,s}^{\text{LiFi}} \geq \phi^{\text{Hybrid}} \psi^{\text{Hybrid}}, \\ \text{C7: } & P_{\text{WiFi}} + P_{\text{LiFi}} \leq \psi^{\text{Hybrid}}, \\ & \text{C1, C2, C3 and C4.} \end{aligned} \quad (28)$$

In the optimization problem P2, constraints C6 and C7 are introduced to handle the non-convex constraint C5. Constraint C6 is non-convex because of the coupled optimization variables $\phi^{\text{Hybrid}} \psi^{\text{Hybrid}}$ and its dependence on the rate expressions $R_{k,s}^{\text{WiFi}}$ and $R_{k,s}^{\text{LiFi}}$. We exploit the first-order Taylor expansion to linearize constraint C6 in problem P2 in terms of the coupled optimization variables $\phi^{\text{Hybrid}} \psi^{\text{Hybrid}}$, as shown below. The general form and full derivation of this Taylor expansion are provided in Appendix B-A.

$$\begin{aligned} \sum_{k=1}^K R_{k,s}^{\text{WiFi}} + \sum_{k=1}^K R_{k,s}^{\text{LiFi}} & \geq \phi_{(t)}^{\text{Hybrid}} \psi_{(t)}^{\text{Hybrid}} + \psi_{(t)}^{\text{Hybrid}} (\phi^{\text{Hybrid}} - \phi_{(t)}^{\text{Hybrid}}) \\ & + \phi_{(t)}^{\text{Hybrid}} (\psi^{\text{Hybrid}} - \psi_{(t)}^{\text{Hybrid}}). \end{aligned} \quad (29)$$

where $\phi_{(t)}^{\text{Hybrid}} \psi_{(t)}^{\text{Hybrid}}$ indicates the value of $\phi^{\text{Hybrid}} \psi^{\text{Hybrid}}$ in the t^{th} iteration. Further, to deal with the non-convexity of C6 in P2, it is important to approximate the non-convex rate expressions $R_{k,s}^{\text{WiFi}}$ and $R_{k,s}^{\text{LiFi}}$. For $s \in e\text{MBB}$, the rate expressions have only the Shannon term, that is $S_{k,s}^{\text{WiFi}}$ and $S_{k,s}^{\text{LiFi}}$. While for $s \in \{URLLC, mMTC\}$, the rate expressions have both the Shannon term and the channel dispersion term, that is $S_{k,s}^{\text{WiFi}}, V_{k,s}^{\text{WiFi}}, S_{k,s}^{\text{LiFi}}$, and $V_{k,s}^{\text{LiFi}}$. To convexify C6 in terms of rate expressions, it is vital to obtain a concave

approximation of Shannon's term and a convex approximation of the channel dispersion term.

A. Concave approximation for $S_{k,s}^{\text{WiFi}}$ and $S_{k,s}^{\text{LiFi}}$

We first obtain the concave approximation for $S_{k,s}^{\text{WiFi}}$ and $S_{k,s}^{\text{LiFi}}$ as a function of $\mathbf{f}_{k,s}^{\text{WiFi}}$ and $\mathbf{f}_{k,s}^{\text{LiFi}}$. According to [39], Eq. (20)], a concave approximation of $S_{k,s}^{\text{WiFi}}$ and $S_{k,s}^{\text{LiFi}}$ is given as

$$\begin{aligned} S_{k,s}^{\text{WiFi}} & \geq [S_{k,s}^{\text{WiFi}}]^{(t)} - [\gamma_{k,s}^{\text{WiFi}}]^{(t)} + A_{k,s}^{\text{WiFi}} - B_{k,s}^{\text{WiFi}}, \\ & \triangleq \bar{S}_{k,s}^{\text{WiFi}}, \end{aligned} \quad (30)$$

$$\begin{aligned} S_{k,s}^{\text{LiFi}} & \geq [S_{k,s}^{\text{LiFi}}]^{(t)} - \frac{e}{2\pi} [\gamma_{k,s}^{\text{LiFi}}]^{(t)} + A_{k,s}^{\text{LiFi}} - B_{k,s}^{\text{LiFi}}, \\ & \triangleq \bar{S}_{k,s}^{\text{LiFi}}, \end{aligned} \quad (31)$$

where

$$\begin{aligned} A_{k,s}^{\text{WiFi}} & = \frac{2 \Re \left\{ \left((\mathbf{h}_{k,s}^{\text{WiFi}})^H (\mathbf{f}_{k,s}^{\text{WiFi}})^{(t)} \right)^H \left((\mathbf{h}_{k,s}^{\text{WiFi}})^H \mathbf{f}_{k,s}^{\text{WiFi}} \right) \right\}}{[\mathbf{Y}_{k,s}^{\text{WiFi}}]^{(t)}}, \\ B_{k,s}^{\text{WiFi}} & = \frac{[\mathbf{X}_{k,s}^{\text{WiFi}}]^{(t)}}{[\mathbf{Y}_{k,s}^{\text{WiFi}}]^{(t)} \left([\mathbf{Y}_{k,s}^{\text{WiFi}}]^{(t)} + [\mathbf{X}_{k,s}^{\text{WiFi}}]^{(t)} \right)} ([\mathbf{X}_{k,s}^{\text{WiFi}}] + [\mathbf{Y}_{k,s}^{\text{WiFi}}]), \\ A_{k,s}^{\text{LiFi}} & = \frac{2e \Re \left\{ \left((\mathbf{h}_{k,s}^{\text{LiFi}})^T (\mathbf{f}_{k,s}^{\text{LiFi}})^{(t)} \right)^T \left((\mathbf{h}_{k,s}^{\text{LiFi}})^T \mathbf{f}_{k,s}^{\text{LiFi}} \right) \right\}}{2\pi [\mathbf{Y}_{k,s}^{\text{LiFi}}]^{(t)}}, \\ B_{k,s}^{\text{LiFi}} & = \frac{e [\mathbf{X}_{k,s}^{\text{LiFi}}]^{(t)}}{\left(2\pi [\mathbf{Y}_{k,s}^{\text{LiFi}}]^{(t)} \right) \left(2\pi [\mathbf{Y}_{k,s}^{\text{LiFi}}]^{(t)} + e [\mathbf{X}_{k,s}^{\text{LiFi}}]^{(t)} \right)} (e [\mathbf{X}_{k,s}^{\text{LiFi}}] + 2\pi [\mathbf{Y}_{k,s}^{\text{LiFi}}]). \end{aligned} \quad (32)$$

The terms $[\gamma_{k,s}^{\text{WiFi}}]^{(t)}$, $[\gamma_{k,s}^{\text{LiFi}}]^{(t)}$, $[S_{k,s}^{\text{WiFi}}]^{(t)}$, $[S_{k,s}^{\text{LiFi}}]^{(t)}$, $[X_{k,s}^{\text{WiFi}}]^{(t)}$, $[X_{k,s}^{\text{LiFi}}]^{(t)}$, $[Y_{k,s}^{\text{WiFi}}]^{(t)}$, and $[Y_{k,s}^{\text{LiFi}}]^{(t)}$ denote the values of $\gamma_{k,s}^{\text{WiFi}}$, $\gamma_{k,s}^{\text{LiFi}}$, $S_{k,s}^{\text{WiFi}}$, $S_{k,s}^{\text{LiFi}}$, $X_{k,s}^{\text{WiFi}}$, $X_{k,s}^{\text{LiFi}}$, $Y_{k,s}^{\text{WiFi}}$, and $Y_{k,s}^{\text{LiFi}}$ in the t^{th}

iteration, respectively, under the trust-region constraint given by

$$|(\mathbf{h}_{k,s}^{\text{WiFi}})^H \mathbf{f}_{k,s}^{\text{WiFi}}|^2 > 0, \quad (34)$$

$$e * |(\mathbf{h}_{k,s}^{\text{LiFi}})^\top \mathbf{f}_{k,s}^{\text{LiFi}}|^2 > 0, \quad (35)$$

where $|(\mathbf{h}_{k,s}^{\text{WiFi}})^H \mathbf{f}_{k,s}^{\text{WiFi}}|^2$ and $|(\mathbf{h}_{k,s}^{\text{LiFi}})^\top \mathbf{f}_{k,s}^{\text{LiFi}}|^2$ can be approximated by the first-order Taylor approximation as

$$2 \Re \left[((\mathbf{h}_{k,s}^{\text{WiFi}})^H (\mathbf{f}_{k,s}^{\text{WiFi}})^{(t)})^H ((\mathbf{h}_{k,s}^{\text{WiFi}})^H \mathbf{f}_{k,s}^{\text{WiFi}}) \right] - |(\mathbf{h}_{k,s}^{\text{WiFi}})^H (\mathbf{f}_{k,s}^{\text{WiFi}})^{(t)}|^2 > 0, \quad (36)$$

$$e \left\{ 2 \left[((\mathbf{h}_{k,s}^{\text{LiFi}})^\top (\mathbf{f}_{k,s}^{\text{LiFi}})^{(t)}) ((\mathbf{h}_{k,s}^{\text{LiFi}})^\top \mathbf{f}_{k,s}^{\text{LiFi}}) \right] - |(\mathbf{h}_{k,s}^{\text{LiFi}})^\top (\mathbf{f}_{k,s}^{\text{LiFi}})^{(t)}|^2 \right\} > 0. \quad (37)$$

The first-order Taylor approximations used in Eqs. (36) and (37), which enable tractable reformulation of the trust region constraints, are derived in Appendix B-B.

B. Convex approximation for $V_{k,s}^{\text{WiFi}}$ and $V_{k,s}^{\text{LiFi}}$

We can write $V_{k,s}^{\text{WiFi}}$ and $V_{k,s}^{\text{LiFi}}$ as

$$V_{k,s}^{\text{WiFi}} = \chi_{k,s}^{\text{WiFi}} \sqrt{D_{k,s}^{\text{WiFi}}}, \quad (38)$$

and

$$V_{k,s}^{\text{LiFi}} = \chi_{k,s}^{\text{LiFi}} \sqrt{0.5 D_{k,s}^{\text{LiFi}}}, \quad (39)$$

where $\chi_{k,s}^{\text{WiFi}}$ and $\chi_{k,s}^{\text{LiFi}} = \frac{Q^{-1}(\epsilon)}{\sqrt{L_k}}$. $D_{k,s}^{\text{WiFi}} = 1 - \frac{1}{(1+\gamma_{k,s}^{\text{WiFi}})^2}$, and $D_{k,s}^{\text{LiFi}} = 1 - \frac{1}{(1+\frac{e}{2\pi}\gamma_{k,s}^{\text{LiFi}})^2}$. In Eq. (38) and (39), the optimization variables exist in terms of $D_{k,s}^{\text{WiFi}}$ and $D_{k,s}^{\text{LiFi}}$. Both terms are in the form $\sqrt{x}$. Since $f(x) = \sqrt{x}$ is concave for $x > 0$, we apply a first-order Taylor approximation around a feasible point $x^{(t)}$ to obtain a convex upper bound. The derivation of this approximation is provided in Appendix B-C. Using this, we obtain:

$$\sqrt{D_{k,s}^{\text{WiFi}}} \leq \frac{\sqrt{D_{k,s}^{\text{WiFi}}(t)}}{2} + \frac{D_{k,s}^{\text{WiFi}}}{2\sqrt{D_{k,s}^{\text{WiFi}}(t)}}, \quad (40)$$

which can be further approximated as

$$\sqrt{D_{k,s}^{\text{WiFi}}} \leq \frac{\sqrt{D_{k,s}^{\text{WiFi}}(t)}}{2} + \frac{1}{2\sqrt{D_{k,s}^{\text{WiFi}}(t)}} - \frac{1}{2\sqrt{D_{k,s}^{\text{WiFi}}(t)}} \frac{1}{(1+\gamma_{k,s}^{\text{WiFi}})^2}. \quad (41)$$

By expanding the SINR-related term, we obtain

$$\begin{aligned} \sqrt{D_{k,s}^{\text{WiFi}}} &\leq \frac{\sqrt{D_{k,s}^{\text{WiFi}}(t)}}{2} + \frac{1}{2\sqrt{D_{k,s}^{\text{WiFi}}(t)}} - \frac{1}{2\sqrt{D_{k,s}^{\text{WiFi}}(t)}} \\ &\times \left[\frac{\left(\sum_{j \neq k} |(\mathbf{h}_{k,s}^{\text{WiFi}})^H \mathbf{f}_{j,s}^{\text{WiFi}}|^2 + (\sigma_{k,s}^{\text{WiFi}})^2 \right)^2}{\left(\sum_{k=1}^K |(\mathbf{h}_{k,s}^{\text{WiFi}})^H \mathbf{f}_{k,s}^{\text{WiFi}}|^2 + (\sigma_{k,s}^{\text{WiFi}})^2 \right)^2} \right]. \end{aligned} \quad (42)$$

Equivalently, the above can be compactly expressed as

$$\begin{aligned} \sqrt{D_{k,s}^{\text{WiFi}}} &\leq \frac{\sqrt{D_{k,s}^{\text{WiFi}}(t)}}{2} + \frac{1}{2\sqrt{D_{k,s}^{\text{WiFi}}(t)}} - \frac{1}{2\sqrt{D_{k,s}^{\text{WiFi}}(t)}} \\ &\times \left(\frac{(Y_{k,s}^{\text{WiFi}})^2}{(X_{k,s}^{\text{WiFi}} + Y_{k,s}^{\text{WiFi}})^2} \right), \end{aligned} \quad (43)$$

which can be further simplified into the following linear form:

$$\sqrt{D_{k,s}^{\text{WiFi}}} \leq \alpha_{k,s}^{\text{WiFi}} - \beta_{k,s}^{\text{WiFi}} \left(\frac{(Y_{k,s}^{\text{WiFi}})^2}{(X_{k,s}^{\text{WiFi}} + Y_{k,s}^{\text{WiFi}})^2} \right), \quad (44)$$

where

$$0 < \beta_{k,s}^{\text{WiFi}} = \frac{1}{2\sqrt{D_{k,s}^{\text{WiFi}}(t)}}, \quad (45)$$

and

$$0 < \alpha_{k,s}^{\text{WiFi}} = \frac{\sqrt{D_{k,s}^{\text{WiFi}}(t)}}{2} + \beta_{k,s}^{\text{WiFi}}. \quad (46)$$

The right-hand side (RHS) of (44) is still nonconvex due to the term $\frac{(Y_{k,s}^{\text{WiFi}})^2}{(X_{k,s}^{\text{WiFi}} + Y_{k,s}^{\text{WiFi}})^2}$; therefore, it is rewritten in product form as

$$\frac{(Y_{k,s}^{\text{WiFi}})^2}{(X_{k,s}^{\text{WiFi}} + Y_{k,s}^{\text{WiFi}})^2} = \frac{(Y_{k,s}^{\text{WiFi}})^2}{(X_{k,s}^{\text{WiFi}} + Y_{k,s}^{\text{WiFi}})} \times \frac{1}{(X_{k,s}^{\text{WiFi}} + Y_{k,s}^{\text{WiFi}})}, \quad (47)$$

and a first-order Taylor approximation is applied to the inverse term to obtain a concave lower bound, as shown in (48). The general form and derivation of this approximation are provided in Appendix B-D.

$$\frac{1}{X_{k,s}^{\text{WiFi}} + Y_{k,s}^{\text{WiFi}}} = \frac{2}{X_{k,s}^{\text{WiFi}}(t) + Y_{k,s}^{\text{WiFi}}(t)} - \frac{X_{k,s}^{\text{WiFi}} + Y_{k,s}^{\text{WiFi}}}{(X_{k,s}^{\text{WiFi}}(t) + Y_{k,s}^{\text{WiFi}}(t))^2}. \quad (48)$$

Under the condition

$$X_{k,s}^{\text{WiFi}} + Y_{k,s}^{\text{WiFi}} \leq 2 \left(X_{k,s}^{\text{WiFi}}(t) + Y_{k,s}^{\text{WiFi}}(t) \right). \quad (49)$$

Substituting Eq. (48) into Eq. (47) yields

$$\begin{aligned} \frac{(Y_{k,s}^{\text{WiFi}})^2}{(X_{k,s}^{\text{WiFi}} + Y_{k,s}^{\text{WiFi}})^2} &= \frac{(Y_{k,s}^{\text{WiFi}})^2}{X_{k,s}^{\text{WiFi}} + Y_{k,s}^{\text{WiFi}}} \left[\frac{2}{X_{k,s}^{\text{WiFi}}(t) + Y_{k,s}^{\text{WiFi}}(t)} \right. \\ &\quad \left. - \frac{X_{k,s}^{\text{WiFi}} + Y_{k,s}^{\text{WiFi}}}{(X_{k,s}^{\text{WiFi}}(t) + Y_{k,s}^{\text{WiFi}}(t))^2} \right]. \end{aligned} \quad (50)$$

By simplifying (50), we obtain

$$\begin{aligned} \frac{(Y_{k,s}^{\text{WiFi}})^2}{(X_{k,s}^{\text{WiFi}} + Y_{k,s}^{\text{WiFi}})^2} &= \frac{(Y_{k,s}^{\text{WiFi}})^2}{X_{k,s}^{\text{WiFi}} + Y_{k,s}^{\text{WiFi}}} \frac{2}{X_{k,s}^{\text{WiFi}}(t) + Y_{k,s}^{\text{WiFi}}(t)} \\ &\quad - \frac{(Y_{k,s}^{\text{WiFi}})^2}{(X_{k,s}^{\text{WiFi}}(t) + Y_{k,s}^{\text{WiFi}}(t))^2}. \end{aligned} \quad (51)$$

$$\frac{(Y_{k,s}^{\text{WiFi}})^2}{(X_{k,s}^{\text{WiFi}} + Y_{k,s}^{\text{WiFi}})^2} = \left(\frac{2 Y_{k,s}^{\text{WiFi}(t)}}{X_{k,s}^{\text{WiFi}(t)} + Y_{k,s}^{\text{WiFi}(t)}} \tau_{k,s}^{\text{WiFi}(t)} - \frac{(Y_{k,s}^{\text{WiFi}(t)})^2}{(X_{k,s}^{\text{WiFi}(t)} + Y_{k,s}^{\text{WiFi}(t)})^2} (X_{k,s}^{\text{WiFi}} + Y_{k,s}^{\text{WiFi}}) \right) \frac{2}{X_{k,s}^{\text{WiFi}(t)} + Y_{k,s}^{\text{WiFi}(t)}} - \frac{(Y_{k,s}^{\text{WiFi}})^2}{(X_{k,s}^{\text{WiFi}(t)} + Y_{k,s}^{\text{WiFi}(t)})^2}. \quad (56)$$

Further simplification of Eq. (56) leads to Eq. (57) as

$$\frac{(Y_{k,s}^{\text{WiFi}})^2}{(X_{k,s}^{\text{WiFi}} + Y_{k,s}^{\text{WiFi}})^2} = \frac{4 Y_{k,s}^{\text{WiFi}(t)}}{(X_{k,s}^{\text{WiFi}(t)} + Y_{k,s}^{\text{WiFi}(t)})^2} \tau_{k,s}^{\text{WiFi}(t)} - \frac{2 (Y_{k,s}^{\text{WiFi}(t)})^2}{(X_{k,s}^{\text{WiFi}(t)} + Y_{k,s}^{\text{WiFi}(t)})^3} (X_{k,s}^{\text{WiFi}} + Y_{k,s}^{\text{WiFi}}) - \frac{(Y_{k,s}^{\text{WiFi}})^2}{(X_{k,s}^{\text{WiFi}(t)} + Y_{k,s}^{\text{WiFi}(t)})^2}. \quad (57)$$

Substituting Eq. (57) into Eq. (44) results in Convex approximation for $D_{k,s}^{\text{WiFi}}$ as follows

$$\sqrt{D_{k,s}^{\text{WiFi}}} \leq \alpha_{k,s}^{\text{WiFi}(t)} - \beta_{k,s}^{\text{WiFi}(t)} \left[\frac{4 Y_{k,s}^{\text{WiFi}(t)}}{(X_{k,s}^{\text{WiFi}(t)} + Y_{k,s}^{\text{WiFi}(t)})^2} \tau_{k,s}^{\text{WiFi}(t)} - \frac{2 (Y_{k,s}^{\text{WiFi}(t)})^2}{(X_{k,s}^{\text{WiFi}(t)} + Y_{k,s}^{\text{WiFi}(t)})^3} (X_{k,s}^{\text{WiFi}} + Y_{k,s}^{\text{WiFi}}) - \frac{(Y_{k,s}^{\text{WiFi}})^2}{(X_{k,s}^{\text{WiFi}(t)} + Y_{k,s}^{\text{WiFi}(t)})^2} \right], \triangleq \sqrt{D_{k,s}^{\text{WiFi}}}. \quad (58)$$

Similarly, the convex approximation for $D_{k,s}^{\text{LiFi}}$ is given in Eq. (59).

$$\sqrt{D_{k,s}^{\text{LiFi}}} \leq \alpha_{k,s}^{\text{LiFi}(t)} - \beta_{k,s}^{\text{LiFi}(t)} \left[\frac{4 Y_{k,s}^{\text{LiFi}(t)}}{(X_{k,s}^{\text{LiFi}(t)} + Y_{k,s}^{\text{LiFi}(t)})^2} \tau_{k,s}^{\text{LiFi}(t)} - \frac{2 (Y_{k,s}^{\text{LiFi}(t)})^2}{(X_{k,s}^{\text{LiFi}(t)} + Y_{k,s}^{\text{LiFi}(t)})^3} (e X_{k,s}^{\text{LiFi}} + 2\pi Y_{k,s}^{\text{LiFi}}) - \frac{(2\pi Y_{k,s}^{\text{LiFi}})^2}{(X_{k,s}^{\text{LiFi}(t)} + Y_{k,s}^{\text{LiFi}(t)})^2} \right], \triangleq \sqrt{D_{k,s}^{\text{LiFi}}}. \quad (59)$$

We now employ the inequality [[39], Eq. 21] to approximate

$\frac{(Y_{k,s}^{\text{WiFi}})^2}{X_{k,s}^{\text{WiFi}} + Y_{k,s}^{\text{WiFi}}}$ as

$$\begin{aligned} \frac{(Y_{k,s}^{\text{WiFi}})^2}{X_{k,s}^{\text{WiFi}} + Y_{k,s}^{\text{WiFi}}} &\geq \frac{2 Y_{k,s}^{\text{WiFi}(t)}}{X_{k,s}^{\text{WiFi}(t)} + Y_{k,s}^{\text{WiFi}(t)}} Y_{k,s}^{\text{WiFi}} \\ &\quad - \frac{(Y_{k,s}^{\text{WiFi}(t)})^2}{(X_{k,s}^{\text{WiFi}(t)} + Y_{k,s}^{\text{WiFi}(t)})^2} (X_{k,s}^{\text{WiFi}} + Y_{k,s}^{\text{WiFi}}). \end{aligned} \quad (52)$$

Similarly, replacing $Y_{k,s}^{\text{WiFi}}$ with $\tau_{k,s}^{\text{WiFi}(t)}$ yields

$$\begin{aligned} \frac{(Y_{k,s}^{\text{WiFi}})^2}{X_{k,s}^{\text{WiFi}} + Y_{k,s}^{\text{WiFi}}} &\geq \frac{2 Y_{k,s}^{\text{WiFi}(t)}}{X_{k,s}^{\text{WiFi}(t)} + Y_{k,s}^{\text{WiFi}(t)}} \tau_{k,s}^{\text{WiFi}(t)} \\ &\quad - \frac{(Y_{k,s}^{\text{WiFi}(t)})^2}{(X_{k,s}^{\text{WiFi}(t)} + Y_{k,s}^{\text{WiFi}(t)})^2} (X_{k,s}^{\text{WiFi}} + Y_{k,s}^{\text{WiFi}}). \end{aligned} \quad (53)$$

Under the condition

$$X_{k,s}^{\text{WiFi}} + Y_{k,s}^{\text{WiFi}} \leq 2 \cdot \frac{X_{k,s}^{\text{WiFi}(t)} + Y_{k,s}^{\text{WiFi}(t)}}{Y_{k,s}^{\text{WiFi}(t)}} \cdot Y_{k,s}^{\text{WiFi}}, \quad (54)$$

where $\tau_{k,s}^{\text{WiFi}(t)}$ denotes the first-order Taylor approximation of $Y_{k,s}^{\text{WiFi}}$ evaluated at iteration t , as derived in Appendix B-B. It is given by

$$\begin{aligned} Y_{k,s}^{\text{WiFi}} &\geq \tau_{k,s}^{\text{WiFi}(t)} = \sum_{j \neq k} \left(2 \Re \left\{ ((\mathbf{h}_{k,s}^{\text{WiFi}})^H \mathbf{f}_{j,s}^{\text{WiFi}(t)})^* ((\mathbf{h}_{k,s}^{\text{WiFi}})^H \mathbf{f}_{k,s}^{\text{WiFi}}) \right\} \right. \\ &\quad \left. - |(\mathbf{h}_{k,s}^{\text{WiFi}})^H \mathbf{f}_{j,s}^{\text{WiFi}(t)}|^2 \right) + (\sigma_{k,s}^{\text{WiFi}})^2. \end{aligned} \quad (55)$$

Putting Eq. (53) in Eq. (51) results in Eq. (56). Subsequently, from Eq. (58),

$$\overline{V_{k,s}^{\text{WiFi}}} = \chi_{k,s}^{\text{WiFi}} \sqrt{D_{k,s}^{\text{WiFi}}}. \quad (60)$$

Similarly, the convex approximation for $D_{k,s}^{\text{LiFi}}$ is derived as in Eq. (59). For

$$0 < \beta_{k,s}^{\text{LiFi}(t)} = \frac{1}{2\sqrt{D_{k,s}^{\text{LiFi}(t)}}}, \quad (61)$$

$$0 < \alpha_{k,s}^{\text{LiFi}(t)} = \frac{\sqrt{D_{k,s}^{\text{LiFi}(t)}}}{2} + \beta_{k,s}^{\text{LiFi}(t)}, \quad (62)$$

and under the condition

$$e X_{k,s}^{\text{LiFi}} + 2\pi Y_{k,s}^{\text{LiFi}} \leq 2 \left(X_{k,s}^{\text{LiFi}(t)} + Y_{k,s}^{\text{LiFi}(t)} \right), \quad (63)$$

$$e X_{k,s}^{\text{LiFi}} + 2\pi Y_{k,s}^{\text{LiFi}} \leq 2 \cdot \frac{X_{k,s}^{\text{LiFi}(t)} + Y_{k,s}^{\text{LiFi}(t)}}{Y_{k,s}^{\text{LiFi}(t)}} \cdot 2\pi Y_{k,s}^{\text{LiFi}}, \quad (64)$$

where

$$D_{k,s}^{\text{LiFi}(t)} = 1 - \frac{1}{\left(1 + \frac{e}{2\pi} \gamma_{k,s}^{\text{LiFi}(t)} \right)^2}, \quad (65)$$

$$Y_{k,s}^{\text{LiFi}(t)} = 2\pi \left(\sum_{j \neq k} \left| (\mathbf{h}_{k,s}^{\text{LiFi}})^\top \mathbf{f}_{j,s}^{\text{LiFi}(t)} \right|^2 + (\sigma_{k,s}^{\text{LiFi}})^2 \right), \quad (66)$$

$$X_{k,s}^{\text{LiFi}(t)} = e \left| (\mathbf{h}_{k,s}^{\text{LiFi}})^\top \mathbf{f}_{k,s}^{\text{LiFi}} \right|^2. \quad (67)$$

The auxiliary variable $\tau_{k,s}^{\text{LiFi}(t)}$ is expressed as

$$\begin{aligned} \tau_{k,s}^{\text{LiFi}(t)} &= 2\pi \left[\sum_{j \neq k} \left(2 \Re \left\{ ((\mathbf{h}_{k,s}^{\text{LiFi}})^\top \mathbf{f}_{j,s}^{\text{LiFi}(t)})^* ((\mathbf{h}_{k,s}^{\text{LiFi}})^H \mathbf{f}_{k,s}^{\text{LiFi}}) \right\} \right. \right. \\ &\quad \left. \left. - |(\mathbf{h}_{k,s}^{\text{LiFi}})^H \mathbf{f}_{j,s}^{\text{LiFi}(t)}|^2 \right) + \sigma_{k,s}^{\text{LiFi}2} \right]. \end{aligned} \quad (68)$$

Subsequently, from Eq. (59), the upper bound of the LiFi-related variable is obtained as

$$\overline{V_{k,s}^{\text{LiFi}}} = \chi_{k,s}^{\text{LiFi}} \sqrt{D_{k,s}^{\text{LiFi}}}. \quad (69)$$

Now, constraint C6 in P2 in term of rate expressions is convex, because we obtained a concave approximation of shanon's term and a convex approximation of channel dispersion term. C6 in convex form can be represented as follows

$$\begin{aligned} \sum_{k=1}^K \overline{R_{k,s}^{\text{WiFi}}} + \sum_{k=1}^K \overline{R_{k,s}^{\text{LiFi}}} &\geq \phi_{(t)}^{\text{Hybrid}} \psi_{(t)}^{\text{Hybrid}} + \psi_{(t)}^{\text{Hybrid}} \left(\phi_{(t)}^{\text{Hybrid}} - \phi_{(t)}^{\text{Hybrid}} \right) \\ &\quad + \phi_{(t)}^{\text{Hybrid}} \left(\psi_{(t)}^{\text{Hybrid}} - \psi_{(t)}^{\text{Hybrid}} \right). \end{aligned} \quad (70)$$

Where, $\overline{R}_{k,s}^{\text{WiFi}} = \overline{S}_{k,s}^{\text{WiFi}} - \overline{V}_{k,s}^{\text{WiFi}}$ and $\overline{R}_{k,s}^{\text{LiFi}} = \overline{S}_{k,s}^{\text{LiFi}} - \overline{V}_{k,s}^{\text{LiFi}}$. Furthermore, C1 in P2 is now convex and can be expressed as

$$\overline{R}_{k,s}^{\text{WiFi}} + \overline{R}_{k,s}^{\text{LiFi}} \geq R_{k,s}^{\min}. \quad (71)$$

Eventually, the optimization problem P2 presented in Eq. (27) can be reformulated as the following convex optimization problems P3 as

$$\text{P3: } \max_{\mathbf{f}^{\text{WiFi}}, \mathbf{f}^{\text{LiFi}}, \phi^{\text{Hybrid}}, \psi^{\text{Hybrid}}} \phi^{\text{Hybrid}} \quad (72)$$

Subject to:

$$\begin{aligned} &\text{C2, C3, C4, C7, (36), (37), (45), (46), (49), (54),} \\ &\text{(61), (62), (63), (64), (70), and (71).} \end{aligned} \quad (73)$$

The reformulated optimization problems in Eq. (72) has been made convex and can now be efficiently solved using MATLAB CVX at the t iteration. This iterative approach ultimately converges to a suboptimal solution for the original problems. Proper scaling of SINR terms is crucial before applying CVX optimization, as it prevents numerical issues, ensuring accurate and stable convergence to optimal solutions. The proposed algorithm is applicable for EE maximization with data transmission from a single transmitter as well, whether WiFi or LiFi. The final sub-optimal solution of the proposed algorithm depends on the initial point, which must be feasible and can be selected either randomly or heuristically [40]. However, using the finite block length rates as given in Eqs. (18) and (19) can lead to negative rates for $\gamma_{k,s}^{\text{WiFi}} \ll 1$ and $\gamma_{k,s}^{\text{LiFi}} \ll 1$. Moreover, the data rate constraint in problem P3 may not be satisfied with a random initial point. To ensure a feasible initial point, we utilize the approach described in Appendix A.

C. Computational Complexity Analysis of the Proposed Algorithm:

The computational complexity of the proposed predict-and-optimize algorithm for hybrid WiFi/LiFi networks is analyzed in two distinct stages: prediction of network slices and optimization of precoding for EE. In the first stage, the computational complexity of using resilient backpropagation for predicting slice types (eMBB, URLLC, mMTC) in a neural network trained on historically monitored KPIs primarily depends on the forward pass through the network. For a model with L layers, where each layer l has n_l neurons, the complexity is $O\left(m \cdot n_1 + \sum_{l=1}^{L-1} n_l \cdot n_{l+1}\right)$, with m representing the input KPIs. This reflects the operations needed to compute the output from the input features, making the model efficient for real-time predictions in hybrid WiFi/LiFi networks. In the second stage, optimization of precoding, the complexity arises from applying sequential convex approximation and inner approximation methods. The convex problem presented in Eq. (76) involves $2KM + 2KL + 2$ scalar optimization variables and $12K + L + 3$ linear constraints and second order cone (SOC) constraints. Consequently, the worst-case per-iteration complexity of this stage, using the interior-point method, is estimated as $O\left(\sqrt{12K + L + 3}(2KM + 2KL + 2)^3\right)$.

D. Convergence Analysis of the EE Optimization Stage

This subsection analyzes the convergence of the second stage, namely EE optimization via slice-aware precoding, as the prediction stage is non-iterative and thus not subject to convergence analysis. The original EE maximization problem formulated in Problem P1 is non-convex due to the fractional objective function and non-linear rate expressions in the constraints. To address this, we reformulated the problem into P2 and then into a tractable convex form P3, by introducing auxiliary variables ϕ^{Hybrid} and ψ^{Hybrid} , representing the EE and total power consumption, respectively. The resulting problem is solved using a Sequential Convex Approximation (SCA) framework combined with inner approximation techniques. In this iterative framework, the non-convex constraint involving the product in $\phi^{\text{Hybrid}}\psi^{\text{Hybrid}}$ in constraint C6 is linearized at each iteration t using first-order Taylor expansion as presented in Eq. (29). Additionally, the rate expressions $R_{k,s}^{\text{WiFi}}$ and $R_{k,s}^{\text{LiFi}}$, which are also non-convex are convexified through careful approximation. The Shannon terms are concavely lower-bounded, while the channel dispersion terms are upper-bounded using Taylor approximations (see Eqs. (30)–(69)). These approximations transform the originally non-convex rate constraints (C1 and C6) into convex forms. Importantly, constraints such as the power budget (C2 and C7) and LiFi LED input signal constraints (C3) are inherently convex, as they involve quadratic or linear norms of the precoding vectors. Latency constraints (C4) are treated as convex by design. Trust region constraints (Eqs. (36), (37), (45), (46), (49), (54), (61), (62), (63), (64)) are also imposed to ensure the validity of all approximations during each iteration. As a result, the proposed SCA algorithm solves a series of convex subproblems at each iteration, with the following key properties:

- Feasibility is maintained throughout all iterations due to proper initialization and conservative approximations;
- The EE objective ϕ^{Hybrid} is monotonically non-decreasing, i.e.,

$$(\phi^{\text{Hybrid}})^{(t+1)} \geq (\phi^{\text{Hybrid}})^{(t)}, \quad \forall t. \quad (74)$$

- The sequence of iterates is guaranteed to converge to a Karush-Kuhn-Tucker (KKT) point of the original non-convex problem under standard assumptions of continuous differentiability and boundedness [37], [38].

Empirical convergence is also validated in Fig. 5, where the algorithm reliably converges within a small number of iterations across all tested configurations.

IV. NUMERICAL SIMULATIONS

A. Key Insights

This subsection summarizes the main findings of our numerical evaluations prior to presenting detailed results:

- The proposed slice-aware EE maximization algorithm converges rapidly, typically within 10–20 iterations, depending on the number of LEDs or antennas deployed.
- Compared to standard ZF and MRT precoding, the proposed algorithm delivers improved energy efficiency performance.

TABLE II
SIMULATION PARAMETERS

Common Parameters	
Room Size	10 m $\times$ 10 m $\times$ 5 m
Height of Hybrid Transmitters	4 m
$P_{\max}^{\text{Hybrid}}$	38 dBm
LiFi Parameters	
Receiver FOV (ϕ_{FOV})	60°
LED Emission Semiangle ($\psi_{1/2}$)	70°
Area of Photodiode (A_D)	1 cm ²
LiFi Bandwidth ($BW_{k,s}^{\text{LiFi}}$)	20 MHz
LiFi PA Efficiency (η^{LiFi})	0.5
PSD of AWGN in LiFi ($\mu_{k,s}^{\text{LiFi}}$)	10^{-19} A ² /Hz
DC Bias ($x_{DC,t}^s$)	$\sqrt{6}$ A
Maximum Permissible Current ($I_{max,t}$)	5 A
Optical Filter Gain (G_f)	1
Photodiode Responsivity (R_D)	0.54 A/W
Refractive Index (r)	1.5
WiFi Parameters	
WiFi Bandwidth ($BW_{k,s}^{\text{WiFi}}$)	10 MHz
Breakpoint Distance (d_{BP})	5 m
Shadow Fading Std. Dev. within d_{BP} (σ_{in})	3 dB
Shadow Fading Std. Dev. beyond d_{BP} (σ_{out})	5 dB
Central Carrier Frequency (f_c)	2.4 GHz
WiFi PA Efficiency (η^{WiFi})	0.5
PSD of AWGN in WiFi ($\mu_{k,s}^{\text{WiFi}}$)	-174 dBm/Hz

- Robust scalability with increasing number of users and access points.
- For the URLLC slice, the model incorporates finite block-length transmission and queueing delay analysis, ensuring compliance with strict latency requirements.

These key insights validate the effectiveness of our approach in optimizing hybrid WiFi/LiFi networks under diverse service demands.

Following the summary of key insights, we now describe the simulation setup used to validate the proposed predict-and-optimize algorithm for energy-efficient service differentiation in a hybrid LiFi/WiFi network. The simulation environment models a room with dimensions of 10 meters in length, 10 meters in width, and 5 meters in height, equipped with both multi-LED LiFi transmitters and multi-antenna WiFi transmitters. The ceiling of the room is organized into a grid pattern, with LEDs positioned at uniform intervals to ensure optimal coverage. The network can serve K users, each equipped with a photodiode and an antenna, randomly distributed within the room. However, for the convenience of analysis, we conducted simulations with $K = 3$ users, unless otherwise stated. Minimum data rate requirements are set according to slice types: 5 bps/Hz for eMBB, and 1 bps/Hz for both URLLC and mMTC. The full list of simulation parameters used in our simulations is summarized in Table II.

Our simulation framework employs the mATRIC to dynamically predict the slice type for each user based on monitored KPIs. These KPIs include a range of critical performance indicators, including latency, reliability, supported technologies, use case categories, and temporal aspects of the network infrastructure. To facilitate accurate slice prediction at mATRIC, we train a deep learning model using historical KPI data at the universal non-RT RIC. This paper extends the dataset as referenced in [36], adapting it to hybrid WiFi/LiFi

networks. The dataset, includes historical KPI data as features and the slice type as label. To prepare this data for modeling, categorical features are converted into a numerical format using one-hot encoding. This process transforms categorical variables into a series of binary columns, each representing a possible category value, thus enabling the model to interpret these features effectively. The label, or output variable, is the slice type, which includes categories such as eMBB, URLLC, and mMTC. The dataset is split into training and testing subsets, with 80% of the data used for training and 20% for testing. The deep learning model is implemented and trained using MATLAB's Neural Network Toolbox. Specifically, we use the resilient backpropagation algorithm, with feedforward neural networks configured to have Rectified Linear Unit (ReLU) activation functions in the hidden layers and a softmax function in the output layer for classification. To prevent overfitting, L2 regularization is applied. The performance of the model is assessed by plotting training and validation accuracy and loss over epochs, as shown in Fig. 3 and Fig. 4. These figures provide insights into the model's capability to accurately predict the appropriate network slice type. The training accuracy of our model is approximately 98 percent for both the training and test datasets, demonstrating its effectiveness in predicting network slices. Additionally, the training loss is relatively low, indicating that the model is performing well in terms of precision and generalization. This trained model can then be utilized by mATRIC for real-time slice selection for users.

Subsequently, the proposed algorithm optimizes precoding vectors for both LiFi and WiFi technologies to maximize EE with predicted slice types for the users. Our iterative algorithm for maximizing EE shows fast convergence towards the optimal solution, as depicted in Fig. 5. The results demonstrate that our approach effectively addresses the problem, with convergence typically occurring in approximately 10 iterations for 9 LEDs, 15 iterations for 16 LEDs, and 20 iterations for 25 LEDs. This pattern indicates that the number of iterations required for convergence scales with the complexity of the system, specifically the number of LEDs involved. These results were plotted for $M = 8$ antennas at the WiFi and varying numbers of LEDs at the LiFi transmitter. The consistent convergence within these iteration ranges highlights the robustness and adaptability of our method across different configurations. Fig. 6 illustrates the power consumption of the Hybrid WiFi/LiFi transmitter during signal transmission for users, as minimized by our proposed algorithm. The figure shows that increasing the number of LEDs at the LiFi transmitter leads to a higher reduction in power consumption compared to using fewer LEDs.

Since no existing work jointly considers EE and service differentiation using network slicing in hybrid WiFi/LiFi systems, we evaluate our proposed algorithm against two standard precoding techniques: ZF and MRT. These serve as fair and widely used baselines for performance benchmarking under the same network and slicing assumptions. Fig. 7 compares the EE of our proposed precoding algorithm for the hybrid network with ZF and MRT precoding. The comparison is conducted with $M = 8$ antennas at the WiFi transmitter

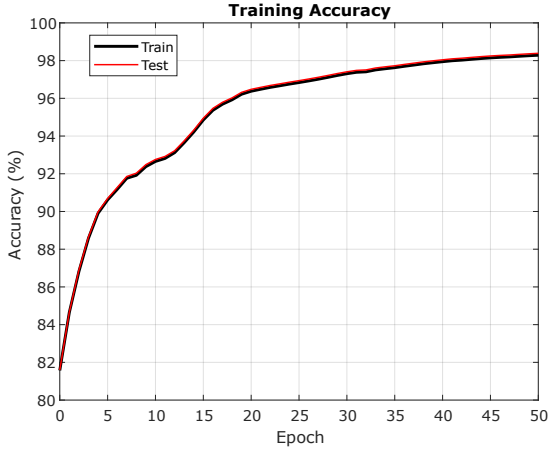


Fig. 3. Training Accuracy of the Proposed Model.

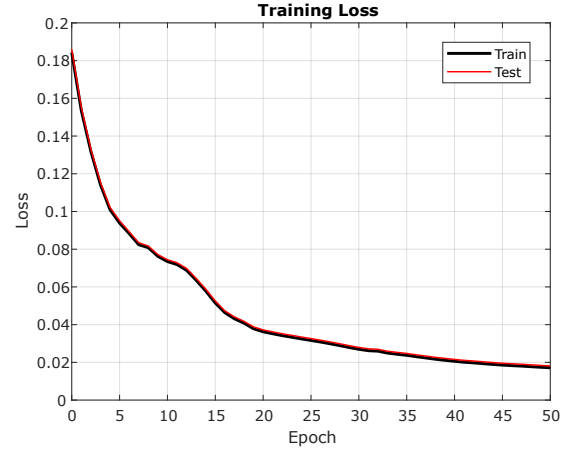


Fig. 4. Training Loss of the Proposed Model.

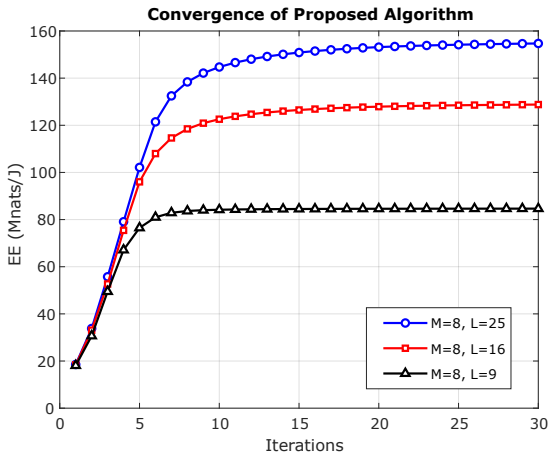


Fig. 5. Convergence of the proposed algorithm for maximizing EE as function of precoding vectors

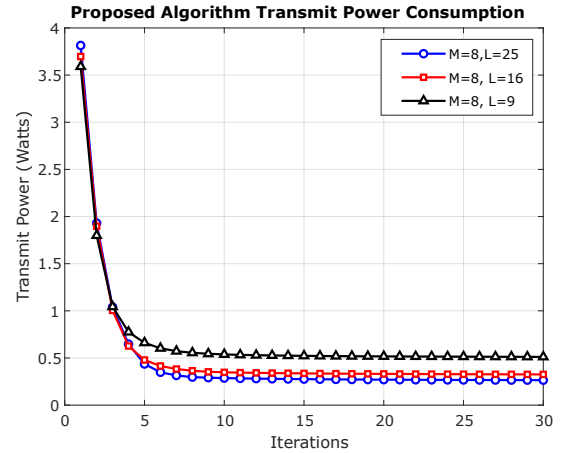


Fig. 6. Transmit power minimization based on proposed algorithm.

and various numbers of LEDs at the LiFi transmitter. The figure clearly shows that our proposed algorithm outperforms the benchmarks in terms of EE. Additionally, it is evident that increasing the number of LEDs at the LiFi transmitter leads to improved EE. Fig. 8 illustrates the EE of the hybrid network using our proposed algorithm as a function of transmission time T^t for URLLC and mMTC slices, which employ finite block lengths for transmission. As anticipated, the EE improves with increasing transmission time because the system sum-rate increases at a faster rate relative to power consumption. This behavior is evident from the rate expressions for URLLC and mMTC. Additionally, Fig. 8 highlights how EE is influenced by stringent latency requirements. Shorter transmission times, necessitated by strict latency constraints, result in lower EE. For system design purposes, selecting transmission time based on the QoS requirements and desired EE is crucial. These results were plotted for $M = 8$ antennas at the WiFi transmitter and varying numbers of LEDs at the LiFi transmitter. Additionally, it can be observed that an increase in the number of LEDs at the LiFi transmitter leads to higher EE with our proposed algorithm. The maximum latency threshold $T_{k,s}^{max}$, is set based on application needs. For URLLC, it is specified as 1 ms to meet stringent reliability and low

latency requirements. For eMBB and mMTC, the thresholds are set at 4 ms and 5 ms, respectively [16]. Within this constraint, transmission time is $T_{k,s}^t = 0.05$ ms, particularly for URLLC, where stringent latency requirements must be met. However, for eMBB and mMTC, longer transmission times can be considered to improve EE, as presented in Fig. 8. The sum of the channel access delay and backhaul delay is $T_{k,s}^a + T_{k,s}^b = 0.1$ ms, while the combined packet reception and processing delays are $T_{k,s}^r + T_{k,s}^p = 0.3$ ms for the hybrid WiFi and LiFi network [35]. The waiting time T_s^w for the users in slice s is modeled as an M/M/1 queue model and can be given as $T_s^w = \frac{1}{(\mu_s^{Hybrid} - \lambda_s)}$, where μ_s^{Hybrid} represents the mean service rate of the hybrid network for serving the users in slice s , and λ_s denote the mean arrival data rate for users in slice s . It is defined as $\lambda_s = \sum_{k=1}^{K_s} \alpha_k$, where α_k represents the arrival data rate of user k in the slice. Therefore, the waiting time of the k^{th} user in slice s is $T_{k,s}^w = \frac{1}{(\mu_{k,s}^{Hybrid} - \alpha_{k,s})}$. Fig. 9 presents the waiting time experienced by a user in a URLLC slice, plotted against the arrival rate of the users and the total number of users being served. The figure demonstrates that the waiting delay increases with both the mean arrival rate (assuming a constant mean service time) and the number of

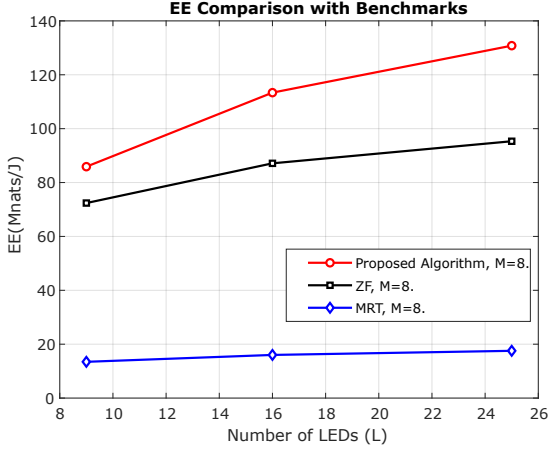


Fig. 7. EE comparison of proposed algorithm with benchmarks

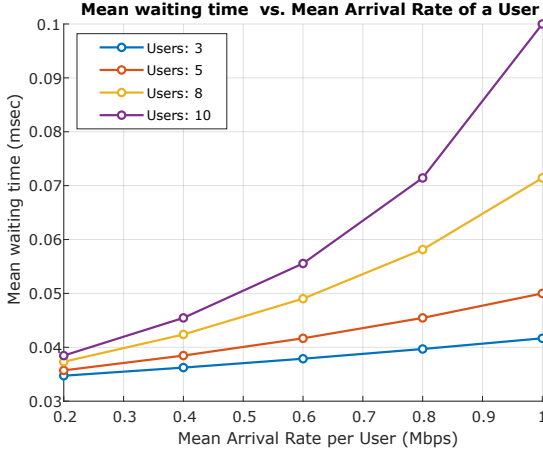


Fig. 9. Mean waiting time vs. mean arrival rate of a user

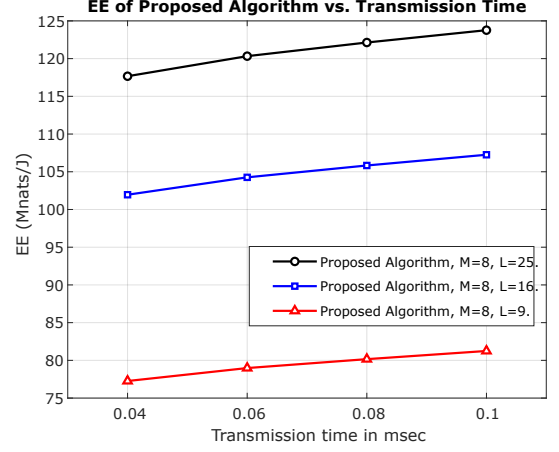


Fig. 8. EE of proposed algorithm vs. transmission time

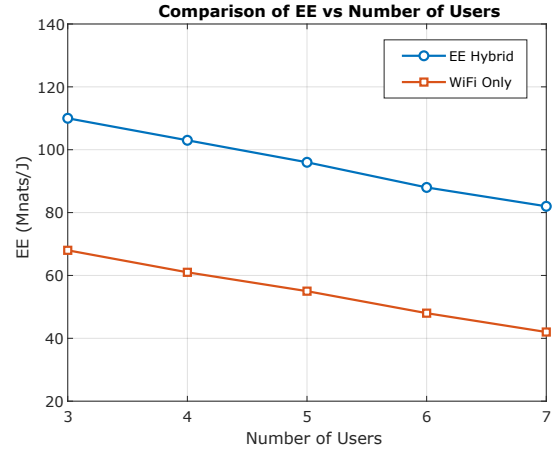


Fig. 10. Comparison of EE vs number of users

users in the slice. Moreover, it is observed that if the waiting time for users in the URLLC slice stays below 0.50 ms, the total latency, including all delays, will comfortably meet the 1 ms requirement, thereby ensuring the stringent latency needs of URLLC are fulfilled. Fig. 10 illustrates a comparative analysis of performance between a fully hybrid LiFi/WiFi system and a WiFi-only system, evaluated through iterative optimization of the proposed algorithm. In the hybrid scenario, users benefit from signals transmitted by both WiFi (with $M = 4$ antennas) and LiFi (with $L = 16$ LEDs). Conversely, the WiFi-only scenario relies solely on WiFi transmitters, equipped with $M = 4$ antennas. The results reveal that the hybrid LiFi/WiFi system significantly outperforms the WiFi-only system in terms of EE. This enhancement highlights the advantages of integrating LiFi with WiFi, offering a more effective and resource-efficient solution compared to using WiFi alone. Additionally, the figure demonstrates a decline in EE as the number of users increases in both systems, particularly in scenarios involving mMTC. This reduction is attributed to the rising demand for power resources, which leads to higher power consumption without a corresponding increase in data rates, ultimately diminishing overall EE.

V. REAL-WORLD APPLICATIONS

Our proposed algorithm applies to any real-world application where users have different service requirements in the hybrid WiFi/LiFi network. For instance, in health-care settings, various services such as patient monitoring through wearable sensors, emergency messages, remote surgery, and telemedicine, including online prescription and consultations have unique demands for data transmission, including capacity, latency and reliability, as shown in Fig. 1. Patient monitoring through wearable sensors depends on mMTC service, which can support many wearable sensors. To ensure accurate patient monitoring, the network should send instructions or updates to these sensors with high reliability, moderate capacity, and latency. Emergency messages are very critical for fast response scenarios and belong to URLLC service. This service demands extremely low latency and high reliability to offer time-sensitive pieces of information such as messages in life-threatening situations. Remote surgery is also related to URLLC because any interruptions in control signals between the surgeon and robotic instruments can lead to life-threatening consequences. While telemedicine services including online prescription and consultations fall under eMBB service, because the transmission of large medical records, i.e. high-

resolution images and video calls demands higher data rates. Our algorithm is designed to manage these varying demands in the hybrid WiFi/LiFi network simultaneously through network slicing, ensuring that each service receives the necessary resources while maximizing the EE of the entire network.

Despite its strong theoretical performance, practical deployment of the proposed hybrid WiFi/LiFi framework involves several critical challenges. Accurate CSI is essential to the effectiveness of the proposed precoding, yet may be degraded by mobility, environmental reflections, or partial blockages, particularly in indoor optical links. In addition, non-ideal LED placement, overlapping coverage regions, and poor spatial diversity can lead to high channel correlation among users, which weakens the interference mitigation capability of the optimized precoding and may reduce convergence efficiency. Hardware misalignment, whether in LED orientation or RF antenna arrays, can further distort channel estimations, reducing the achievable performance gains. Furthermore, coordination across optical and RF domains introduces integration complexity at the control layer, particularly when dual-mode user devices are employed. These deployment-level factors must be addressed to ensure that the proposed framework's EE and service differentiation benefits are reliably achieved in real-world settings.

VI. CONCLUSION

In this paper, we have presented a novel predict-and-optimize algorithm for hybrid WiFi/LiFi networks to address the dual challenges of service differentiation and EE. By using mATRIC for dynamic network slice prediction based on monitored KPIs and employing a deep learning model trained with the resilient backpropagation algorithm, our framework effectively enables real-time slice selection. This approach not only enhances the adaptability of the network to varying user requirements but also ensures that EE is maximized. In the optimization phase, we utilized advanced techniques from sequential convex approximation and the inner approximation method to address the complexities associated with non-convex objective functions and constraints. Our novel approximations and iterative algorithm allow for effective convexification, providing a practical means to achieve near-optimal solutions. The performance evaluation through simulations highlights the robustness of our proposed algorithm. The results demonstrate a significant improvement in EE while maintaining effective service differentiation across hybrid network environments. These findings underscore the potential of our approach to enhance the operational performance of hybrid WiFi/LiFi networks in terms of EE while ensuring service differentiation. This makes our contribution valuable for the ongoing advancements in network optimization and resource management. An interesting direction for future research is the integration of slice-prioritized or weighted utility-based EE objectives, which could enable Service Level Agreement (SLA)-driven optimization across slices while preserving service fairness. Another important direction is to extend the proposed framework to account for imperfect CSI, including the effects of estimation error, quantization, and user mobility. This would

improve robustness and enable practical implementation in dynamic environments.

APPENDIX A

INITIAL FEASIBLE POINT FOR THE PROPOSED ALGORITHM

To determine the initial feasible point $\mathbf{f}_{k,s}^{\text{WiFi}(0)}$, we randomly start from a feasible point for convex power constraint C1-WiFi and iterate the convex problem

$$\text{P0:WiFi: } \max_{\mathbf{f}_{k,s}^{\text{WiFi}}} \left[\min_{k=1,2,\dots,K} \overline{S}_{k,s}^{\text{WiFi}} \right] \quad (75)$$

Subject to:

$$\text{C1-WiFi: } P_{\text{WiFi}} \leq P_{\max}^{\text{WiFi}}, \quad (76)$$

Similarly for the initial point $\mathbf{f}_{k,s}^{\text{LiFi}(0)}$, we randomly start from a feasible point for convex power constraint C1-LiFi and iterate the convex problem

$$\text{P0:LiFi: } \max_{\mathbf{f}_{k,s}^{\text{LiFi}}} \left[\min_{k=1,2,\dots,K} \overline{S}_{k,s}^{\text{LiFi}} \right] \quad (77)$$

Subject to:

$$\text{C1-LiFi: } P_{\text{LiFi}} \leq P_{\max}^{\text{LiFi}}, \quad (78)$$

The Solution of the above problems can be used as initial feasible point for our main convex problem P3.

APPENDIX B

TAYLOR EXPANSIONS USED IN PROBLEM REFORMULATION

This appendix provides the full derivation of the first-order Taylor expansions used to linearize non-convex expressions in the optimization problem reformulated in Section III.

A. Bilinear Product Approximation

To convexify the bilinear term in constraint C6 of Section III, a first-order Taylor approximation is applied. Consider the scalar function:

$$f(x, y) = x \cdot y. \quad (79)$$

We expand $f(x, y)$ around the point $(x^{(t)}, y^{(t)})$ using:

$$\begin{aligned} f(x, y) \approx & f(x^{(t)}, y^{(t)}) + \frac{\partial f}{\partial x} \Big|_{(x^{(t)}, y^{(t)})} (x - x^{(t)}) \\ & + \frac{\partial f}{\partial y} \Big|_{(x^{(t)}, y^{(t)})} (y - y^{(t)}). \end{aligned} \quad (80)$$

The partial derivatives are:

$$\frac{\partial f}{\partial x} = y, \quad \frac{\partial f}{\partial y} = x. \quad (81)$$

Substituting the expressions yields:

$$x \cdot y \approx x^{(t)} y^{(t)} + y^{(t)} (x - x^{(t)}) + x^{(t)} (y - y^{(t)}). \quad (82)$$

This approximation is used in Section III to linearize the product $\varphi_{\text{Hybrid}} \cdot \psi_{\text{Hybrid}}$, allowing constraint C6 to be expressed in a convex form suitable for iterative optimization.

B. Quadratic Inner Product Approximation

In Section III, the constraints in Eqs. (34) and (35) involve received signal power terms of the form $|\mathbf{h}^H \mathbf{f}|^2$ and $(\mathbf{h}^\top \mathbf{f})^2$, which are convex quadratic functions. Although these expressions are convex, the constraints require them to be strictly positive, resulting in a nonconvex feasible region. To enable convex reformulation, each term is approximated via a first-order Taylor expansion around the current iterate $\mathbf{f}^{(t)}$, yielding a linear concave lower bound suitable for use in successive convex approximation.

Let $\mathbf{f} \in \mathbb{C}^n$ (or $\mathbb{R}^n$) be the transmit precoding vector and $\mathbf{h} \in \mathbb{C}^n$ (or $\mathbb{R}^n$) be the corresponding channel vector, where n denotes the dimension of the vectors. We define:

$$f(\mathbf{f}) = |\mathbf{h}^H \mathbf{f}|^2. \quad (83)$$

Letting $z = \mathbf{h}^H \mathbf{f}$, a first-order Taylor expansion around the point $z^{(t)} = \mathbf{h}^H \mathbf{f}^{(t)}$ yields:

$$|z|^2 \approx |z^{(t)}|^2 + 2\Re \left\{ (z^{(t)})^* (z - z^{(t)}) \right\}. \quad (84)$$

Substituting back, we obtain:

$$|\mathbf{h}^H \mathbf{f}|^2 \approx 2\Re \left\{ (\mathbf{h}^H \mathbf{f}^{(t)})^* \cdot \mathbf{h}^H \mathbf{f} \right\} - |\mathbf{h}^H \mathbf{f}^{(t)}|^2. \quad (85)$$

For the real-valued case, relevant to LiFi, this reduces to:

$$(\mathbf{h}^\top \mathbf{f})^2 \approx 2(\mathbf{h}^\top \mathbf{f}^{(t)}) \cdot (\mathbf{h}^\top \mathbf{f}) - (\mathbf{h}^\top \mathbf{f}^{(t)})^2. \quad (86)$$

These approximations are used in Eqs. (36) and (37) of Section III to construct trust region constraints that ensure the validity of the local linearization. The same approximation is used for the interference terms $Y_{k,s}^{\text{WiFi}}$ and $Y_{k,s}^{\text{LiFi}}$, which are sums of received signal powers from other users, as seen in Eqs. (55) and (68), respectively.

C. First-Order Approximation of $\sqrt{x}$ for Convex Reformulation

We approximate the concave function $f(x) = \sqrt{x}$ using a first-order Taylor expansion around a point $x^{(t)} > 0$, yielding:

$$\sqrt{x} \leq \sqrt{x^{(t)}} + \frac{1}{2\sqrt{x^{(t)}}}(x - x^{(t)}), \quad (87)$$

which simplifies to:

$$\sqrt{x} \leq \frac{\sqrt{x^{(t)}}}{2} + \frac{x}{2\sqrt{x^{(t)}}}. \quad (88)$$

This convex upper bound is used in the Section III to approximate $\sqrt{D_{k,s}^{\text{WiFi}}}$ and $\sqrt{D_{k,s}^{\text{LiFi}}}$ in a tractable form.

D. Taylor Approximation for the Inverse Term in Eq. (47)

Although the inverse function is convex, it appears in a product with an affine term in Eq. (47), resulting in a non-convex expression that requires approximation to enable convex reformulation. To linearize the non-convex expression in Eq. (47), we focus on the inverse component:

$$\frac{1}{X_{k,s}^{\text{WiFi}} + Y_{k,s}^{\text{WiFi}}}. \quad (89)$$

This convex term is approximated using a first-order Taylor expansion around a feasible point $x^{(t)}$, resulting in the following concave lower bound:

$$\frac{1}{x} \geq \frac{2}{x^{(t)}} - \frac{x}{(x^{(t)})^2}. \quad (90)$$

Substituting this approximation into Eq. (47), in combination with the affine first factor, yields the concave reformulated expression used in Eq. (48) of the Section III.

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