Deep Learning Based Proactive Optimization for Indoor LiFi Systems with Channel Aging

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Abstract—This paper investigates the channel aging problem of light-fidelity (LiFi) systems. In the LiFi physical layer, the majority of the optimization problems for mobile users are non-convex and require the use of dual decomposition or heuristics techniques. Such techniques are based on iterative algorithms, and often, cause a high processing time at the physical layer. Hence, the obtained solutions are no longer optimal since the LiFi channels are evolving. In this paper, a proactive-optimization approach that can alleviate the LiFi channel aging problem is proposed. The core idea is to design a long-short-term-memory (LSTM) network that is capable of predicting posterior positions and orientations of mobile users, which can be then used to predict their channel coefficients. Consequently, the obtained channel coefficients can be exploited for deriving near-optimal transmission-schemes prior to the intended service-time, which enables real-time service. Through various simulations, the performance of the designed LSTM model is evaluated in terms of prediction accuracy and time. Finally, the performance of the proposed PO approach is investigated in the sum rate maximization problem of multiuser cell-free LiFi systems with quality-of-service constraints, where a performance gap of less than 7% is achieved, while eliminating up to 100% of the online processing-time.

Index Terms—LiFi, LSTM, mobile users, prediction, proactive optimization, VLC, random orientation.

I. INTRODUCTION

A. Motivation

As the fifth generation (5G) cellular systems are currently under deployment, researchers from both academia and industry started shaping their vision on how the upcoming sixth generation (6G) would be [1]. The main goals of 6G networks is not only to fill the gap of the original and unfulfilled promises of 5G or to keep up with the continuous emergence of the Internet of-Things (IoTs) networks but also to be able to handle the exponential increase of both the number of devices connected to the Internet and the total data traffic [2]. Therefore, 6G networks must urgently provide high data rates, seamless connectivity, ubiquitous coverage and ultralow latency communications in order to reach the preset targets [2]. Researchers from both industry and academia are trying to explore new network architectures, new transmission techniques and higher frequency bands, such as the millimeter wave (mmWave), the terahertz (THz), the infrared and the visible light bands, to meet these high requirements [2].

LiFi offers a number of important benefits that have made it favorable for 6G networks [4]. These include the very large, unregulated bandwidth available in the visible light spectrum, high energy efficiency [5], the straightforward deployment that uses off-the-shelf light emitting diode (LED) and photodiode (PD) devices at the transmitter and receiver ends, respectively, and enhanced security as light does not penetrate through opaque objects [6].

The availability of location and data of mobile terminals at the communications stations (access points (APs) and base stations (BSs)), i.e., their knowledge by the telecommunications operators, has become a key factor in enabling 6G networks [7]. Such information enables better estimation of the quality of the wireless links, which can improve the resource management and provide new location-based services [3]. In indoor applications, positioning systems using indoor wireless signals, such as wireless-fidelity (Wi-Fi) [9], Bluetooth [10], radio frequency identification (RFID), mmWave [11], infrared and visible light [12], to improve the performance of indoor positioning. Over the past few years, many algorithms for LiFi-based indoor positioning have been proposed and verified by experiments. LiFi-based indoor positioning systems have shown to be more accurate (0.1-0.35 m positioning error) when compared to Wi-Fi (1-7 m), Bluetooth (2-5 m), and other technologies [13].

In addition to the knowledge of user equipment (UE) position, the knowledge of UE orientation is also a crucial factor, particularly for indoor localization applications such as smart factories and smart/precision agriculture [14], [15]. Although Wi-Fi and Bluetooth are the most utilized positioning systems, which have already been widely deployed in current smart devices, they cannot satisfy the requirements of the above applications (joint UE position and orientation) since their localization performance suffers from the limited number of available APs in their local area [16]. Accordingly, novel and accurate position and orientation estimation solutions are highly demanded. Nevertheless, it is expected that implementing novel position and orientation techniques based on LiFi technology will have a great potential, which has encouraged both academia and industry to actively pursue [17].

B. Recent Advances and Limitations

Unlike in conventional radio frequency (RF) wireless systems, the OWC channel is not isotropic, meaning that the
orientation of both optical transmitters and receivers affects the wireless channel gain significantly [18]. Due to this, in the context of LiFi technology, the joint knowledge of UE position and orientation is a crucial factor for channel estimation and resource tasks [19]. For this purpose, novel and accurate position and orientation estimation solutions were recently proposed in the literature [19]–[21]. An inertial measurement unit (IMU) was required in [20] to measure the UE tilt angle for position estimation. In [21], a simultaneous position and orientation (SPAO) algorithm for indoor LiFi users with an unknown LED emission power is proposed. This approach is based on the received signal strength (RSS) technique where an iterative algorithm for jointly estimating the UE position and orientation was developed. In [19], a deep learning (DL) based joint position and orientation estimation technique was proposed. Specifically, two different artificial neural networks (ANNs), which are a multiple layer perceptron (MLP) and a convolution neural network, were designed and optimized to estimate the 3D position and orientation of a LiFi UE based on its RSS values.

The joint position and orientation estimation techniques proposed in the LiFi literature (such as in [19]–[21] and references therein) are limited to the case of stationary UEs. By definition, a LiFi UE is stationary if its position and orientation are almost constant during several time slots, such as the case of a user that is browsing or watching streaming video while sitting [22]. In such a case, using the proposed estimation techniques in the literature, the position and orientation of each LiFi UE in the network are estimated and then exploited to determine the instantaneous channel state information of the wireless links, which can be then fed into any resource/power allocation or AP selection problem to serve the different LiFi UEs in the network within a certain time horizon. However, the aforementioned estimation techniques cannot be applied to the case of mobile UEs as explained in the following. By definition, a LiFi UE is mobile if its position and/or orientation are changing over consecutive time slots, such as the case of a user that is browsing or watching streaming video while walking [22]. However, at the LiFi physical layer, the majority of the invoked optimization problems are non-convex, e.g., maximizing throughput by means of power control, multi-user spectrum optimization in multi-carrier systems, optimal beamforming for sum rate maximization, to name only a few [23]. These problems may be solved using dual decomposition or heuristic techniques that require iterative algorithms, which induces a certain processing delay at the LiFi physical layer [23]. However, for the case of mobile LiFi users, such processing delay may exceed the maximum amount of time allocated to serve all the mobile users, and therefore, cannot be tolerated. In fact, since users are mobile, they might change their instantaneous positions and/or orientation within the processing time. Consequently, their channel coefficients may evolve within the processing time and their previously estimated channel coefficients are no longer accurate, which makes the obtained solution no longer optimal after the processing time and this can lead to performance degradation. This problem is known as channel aging, i.e., the LiFi channel coefficients are outdated after the optimization time, which is a very known problem in the wireless and mobile communication literature [24], [25].

C. Contributions and Outcomes

Against the above background, a proactive optimization (PO) approach is proposed to overcome the aforementioned channel aging problem. Considering a certain resource/power optimization problem with respect to a certain transmission strategy and a certain performance metric, the proposed PO approach consists of proactively solving the considered problem and determining near-optimal schemes prior to the arrival of the intended service time. Given a certain number of prior time slots $N$ and a certain number of posterior time slots $L$, the operation of the proposed PO approach can be summarized as follows. First, at each time slot $t > 0$, the LiFi controller collects $N$ RSS values of each time LiFi UE during the time interval $[t - N + 1, t]$. Second, the collected RSS values of each LiFi UE are fed into a prediction unit that can predict its 3D position and orientation associated to the posterior time slot $t + L$. Then, the predicted 3D position and orientation of the mobile UEs are exploited to predict their channel coefficients relative to time slot $t + L$. These predicted channel coefficients are fed into the considered optimization problem in order to solve it within the time interval $[t, t + L]$. Consequently, near-optimal solution can be obtained prior to the intended service time slot $t + L$ without any processing delay, and therefore, the aforementioned channel aging problem can be alleviated.

One key component in the proposed PO approach is the prediction unit that can predict the posterior 3D position and orientation of each UE based on its prior received RSS values. For this task, DL techniques are invoked. In this context, the design of the prediction unit consists of two different phases, an offline phase and an online phase. In the offline phase, a large number of random sequences of 3D position and orientation with size $N + L$ time steps are generated using the experimental-based orientation-based random waypoint (ORWP) mobility model [18], [22], [26]. Then, the received SNR values at the APs associated to the first $N$ time steps for each sequence are processed and recorded into a dataset as features. On the other hand, the 3D position and orientation relative to time steps $[N + 1, ]$ are recorded into the same dataset as labels. Afterwards, based on the obtained dataset, a long-short-term-memory (LSTM) network is designed and trained in order to map the posterior received SNR values with their associated posterior 3D positions and orientations. In the online phase, once the LSTM model is trained and optimized, the obtained model is deployed at the APs. The APs receive signals from each UE, calculated its SNR values, and then the APs controller applies the trained LSTM model to the posterior 3D position and orientation of the UE.

The performance of the designed LSTM model, in terms of prediction error, precision and computational time, is compared with an optimized CNN model, which is the best ML-based fingerprinting approach in estimating the 3D position and orientation of LiFi UEs reported in the literature [19]. In addition, as an application of the proposed PO approach, a typical optimization problem is considered, which aims at
maximizing the sum-rate of a multiuser cell-free LiFi system with respect to the weights of zero-forcing (ZF) precoding technique while guaranteeing a certain (QoS) for each LiFi UE. The formulated optimization problem is a non-linear and non-convex, which is difficult to be solved in a straightforward manner. To deal with this issue, the proposed PO approach is applied and the formulated problem is solved proactively using the convex-concave procedure (CCP). Simulation results demonstrate a gap of 0.9% between the performance of the exact LiFi channel coefficients and the one of the predicted channel coefficients, while saving up to 100% in the computational time, and therefore, a near-optimal real-time service of the LiFi mobile UEs.

D. Outline and Notations

The rest of the paper is organized as follows. The system model and problem statement are presented in Section II. Section III presents the proposed PO approach. Sections IV presents the prediction of the 3D position and orientation of LiFi UEs. Section V presents a typical application of the proposed PO approach, that is the proactive sum-rate maximization of multiuser cell free LiFi systems. Sections VI and VII present the simulation results and the conclusion, respectively.

The notations adopted throughout the paper are summarized in Table I. In addition, upper case bold characters denote matrices, whereas lower case bold characters denote vectors. \((\cdot)^T\) denotes the transpose operator. For every two integers \(a\) and \(b\) with \(a < b\), \([a, b]\) denote the discrete interval of integers between \(a\) and \(b\). \(||\cdot||_\infty\) denotes the infinity norm operator. The function \(U_{[a,b]}(\cdot)\) denotes the unit step function within \([a,b]\) for every two real numbers \(a\) and \(b\) such that \(a < b\), i.e., for all \(x \in \mathbb{R}\), \(U_{[a,b]}(x) = 1\) if \(x \in [a,b]\), and 0 otherwise. Finally, for \(N \in \mathbb{N}\), \(\mathbf{0}_N\) and \(\mathbf{1}_N\) denote the all zeros and all ones \(N \times 1\) vector, respectively.

II. System Model and Problem Statement

A. System Setup

We consider the indoor LiFi system shown in Fig. 1 which consists of a room of size \(L \times W \times H\), where \(L\), \(W\) and \(H\) denote the length, the width and the height of the room, respectively. The LiFi system is equipped with \(M\) APs installed at the ceiling of the room. Each AP is down-facing and is equipped with one LED and one PD adjacent to each other, where the LED is used for illumination and downlink data transmission simultaneously and the PD is used for uplink data reception. The \(M\) APs are controlled by a central control unit call LiFi controller, which is responsible for monitoring the data transmission and reception at the APs. Within this indoor system, \(K\) mobile LiFi users are communicating simultaneously (within the same time/frequency resource block) with the APs, where each user is equipped with a LiFi-enabled UE and is moving following a certain trajectory. In addition, during the movements of users, each UE has a random orientation over time, i.e., at each point of the trajectory of each user, the orientation of its associated UE is random. Moreover, each UE is equipped with a single infrared LED and a single PD that are used for data transmission and reception in the downlink and uplink phases, respectively. The communication between the APs and each UE is bidirectional. Specifically, in the downlink, the APs employ the visible light spectrum for transmitting the information and each UE receives this information through its PD, whereas in the uplink, the IR-LED of each UE transmits the information using the IR spectrum and the APs detect the transmitted signals through their respective PDs. In this system, there is no interference between the downlink and uplink transmissions and the two phases can occur simultaneously.

B. Transmission Model

In this system model, we focus on the downlink transmission, where the intensity-modulation direct-detection is considered. For all \(k \in [1,K]\), the downlink received signal at the \(kth\) UE at each time slot \(t > 0\) is expressed as \([26]\),

\[
y_k(t) = \lambda_k h_k^T(t) s(t) + n_k(t),
\]

where \(\lambda_k = R_k \eta_d\), in which \(R_k\) (A/W) is the responsivity of the UE’s PD and \(\eta_d\) (W/A) is the current-to-power conversion efficiency of the LEDs of the APs. For all \(k \in [1,K]\), \(h_k(t) = [h_{k,1}(t), h_{k,2}(t), ..., h_{k,M}(t)]^T\) represents the instantaneous downlink \(M \times 1\) channel gain vector between the
APs and the $k$th UE, where for all $i \in [1, M]$, $h_{k,i}(t)$ represents the instantaneous total channel gain of the wireless link between the $i$th AP and the PD of the $k$th UE, which includes both the line-of-sight (LOS) and the non-line-of-sight (NLOS) components and its model is detailed in Appendix A. In addition, $s(t)$ represents the $M \times 1$ information-bearing signal broadcast by the APs at time slot $t$, which contains a mixture of the data of the $K$ users. Moreover, for all $k \in [1, K]$, $n_k(t)$ is the instantaneous additive white Gaussian noise (AWGN) experienced at the PD of the $k$th UE, which is $\mathcal{N}(0, \sigma_d^2)$ distributed, where $\sigma_d^2 = N_0 B$, where $N_0$ is the noise power spectral density and $B$ is the bandwidth of the system.

The performance of the considered LiFi system depends heavily on the instantaneous $K \times M$ channel matrix $\mathbf{H}(t) = [h_{11}(t), h_{12}(t), ..., h_{kM}(t)]^T$, which in turn depends on the positions of the APs as well as the instantaneous 3D position and orientation of each UE [19]. Basically, for $k \in [1, K]$, the instantaneous 3D position of the $k$th user is characterized by its instantaneous coordinates $(x_k(t), y_k(t), z_k(t))$ in the Cartesian coordinate system $(X, Y, Z)$ shown in Fig. 1. Nevertheless, wearable and hand-held devices, such as smartphones, are prone to random changes in orientation due to not only the user’s hand motion but also to its random trajectory. In this study, we focus on these types of devices and incorporate the random orientation in our analysis. In this case, for all $k \in [1, K]$, the orientation of the $k$th LiFi UE is fully characterized in three dimensions through the elemental instantaneous rotation angles, which are the yaw angle $\alpha_k(t) \in [0^\circ, 360^\circ]$, the pitch angle $\beta_k(t) \in [-180^\circ, 180^\circ]$, and the roll angle $\gamma_k(t) \in [-90^\circ, 90^\circ]$ [27]. At each time slot $t$, and as shown in Fig. 2, $\alpha_k(t)$, $\beta_k(t)$ and $\gamma_k(t)$ denote the rotation angles about the $Z$-axis, the $X$-axis and the $Y$-axis, respectively. According to the Euler’s rotation theorem, any rotation matrix can be expressed by $\mathbf{R}_z(\gamma_k(t)) = \mathbf{R}_y(\beta_k(t)) \mathbf{R}_x(\alpha_k(t))$, where $\mathbf{R}_x(a(t))$, $\mathbf{R}_y(b(t))$ and $\mathbf{R}_z(c(t))$ are expressed in (2) on top of next page. Hence, for all $k \in [1, K]$, the normal vector of the $k$th UE’s PD after performing the rotation at time slot $t$ can be described by $n_k^{\text{PD}}(t) = \mathbf{R}_3(t)\mathbf{n}_r$, where $\mathbf{n}_r$ is the orientation vector of the PD when the $k$th UE is at the standard position, as shown in Fig. 2(a).

C. Problem Statement

From a physical layer point of view, any communication scheme, in order to be efficient, needs to be optimized with respect to its decision parameters. For the considered LiFi system, the strongest component in such optimization is the instantaneous channel matrix $\mathbf{H}(t)$. In this context, assuming that matrix $\mathbf{H}(t)$ is perfectly known at the LiFi controller at each time slot $t$, the majority of the optimization frameworks that can be considered, such as power allocation, bandwidth allocation, precoding/beamforming and AP selection, etc, are generally complex to solve and time-consuming, such as in [28]–[33] to name a few. This class of problems may be solved using dual decomposition techniques or heuristic approaches that require iterative algorithms, and therefore, cannot be computed in real time due to high computational load [23].

![Fig. 2: Orientation of a mobile device: (a) normal position, (b) yaw rotation with angle $\alpha$, about the $z$-axis (c) pitch rotation with angle $\beta$, about the $x$-axis and (d) roll rotation with angle $\gamma$, about the $y$-axis.](image)

In other words, the aforementioned optimization techniques that can be applied require a processing time that may exceed the maximum amount of time allocated to serve all the mobile users [23].

Let us consider an optimization problem $\mathcal{P}[\mathbf{H}(t)]$ that aims at enhancing the performance of the LiFi system at hand at each time slot $t$, with respect to a certain performance metric, such as sum-rate maximization, minimum rate maximization, age of information (AoI) or latency minimization, etc. In addition, let $\Delta t$ denote the processing time required to solve the optimization problem $\mathcal{P}[\mathbf{H}(t)]$ at each time slot $t$, which increases as the number of mobile users and/or APs increases. Within the time interval $\Delta t$, the channel matrix of $\mathbf{H}$ evolves from $\mathbf{H}(t)$ to $\mathbf{H}(t + \Delta t)$, since the users are mobile and may have changed their instantaneous positions and orientations during the time interval $\Delta t$. In this case, the obtained solution from solving problem $\mathcal{P}[\mathbf{H}(t)]$ at time slot $t$ may no longer be optimal after the optimization time $\Delta t$. In other words, the obtained solution, which is optimal for $\mathbf{H}(t)$, is not optimal for $\mathbf{H}(t + \Delta t)$ and can imply a performance loss to the system. This problem is known as channel aging, i.e., the channel matrix $\mathbf{H}(t)$ is outdated at time slot $t + \Delta t$, and this is actually a very known problem in the wireless and mobile communication literature, especially for massive MIMO systems [24], [25]. Based on the above discussion, a PO approach is proposed to overcome the aforementioned channel aging problem, which will be presented in the following section.

III. PROPOSED PO APPROACH

In this section, the proposed PO technique is presented. The basics of the proposed approach will be presented first. Then, its detailed implementation is investigated.

A. Proposed Approach

Let $L \in \mathbb{N}\setminus\{0\}$ denote a posterior time slot index and let us consider an optimization problem $\mathcal{P}[\mathbf{H}(t + L)]$ that needs to be solved at each time slot $t + L$. In order to
overcome the channel aging problem discussed in Section II-C, an alternative approach is to solve problem $\mathcal{P} \{ \mathbf{H}(t+L) \}$ prior to the occurring of the target time slot $t+L$. Precisely, the proposed PO approach consists first of predicting the channel matrix $\mathbf{H}(t+L)$ at time slot $t$, which is denoted by $\hat{\mathbf{H}}(t+L)$. Then, the optimization problem $\mathcal{P} \{ \hat{\mathbf{H}}(t+L) \}$ is solved within the time interval $[t, t+L]$. In this case, a suboptimal solution is obtained and can be employed in serving the cellular users at time slot $t+L$, without any processing delay at time slot $t+L$. This will beat indeed the raised problem of channel aging.

Fig. 3 presents the procedure of the proposed PO approach. As shown in this figure, it consists mainly of three consecutive phases, which are: 1) RSS collection phase, 2) Prediction phase, and 3) Optimization phase. For the ease of reading, we start with the following notations.

Notations 1. For $k \in [1, K]$, we denote by $\mathbf{p}_k(t) = [x_k(t), y_k(t), \sigma_k(t), \alpha_k(t), \beta_k(t), \gamma_k(t)]$ the $1 \times 6$ vector that contains the exact instantaneous 3D position and orientation vector of the $k$th UE at time slot $t$. Accordingly, we denote by $\hat{\mathbf{p}}_k(t)$ the predicted 3D position orientation of the $k$th UE at time slot $t$, respectively.

The details of each phase of the proposed PO approach are presented in the following subsections.

B. RSS Collection Phase

In this phase, $N \in \mathbb{N} \setminus \{0\}$ uplink RSS values for each UE are collected over the time slots $[t - N + 1, t]$. At each time slot $j \in [t - N + 1, t]$ and for all $k \in [1, K]$, the $k$th UE has an instantaneous 3D position and orientation vector $\mathbf{p}_k(j)$. First, in order to cancel any inter-user interference in this phase, the total bandwidth $B$ is equally divided over all $K$ UEs for the uplink transmissions. At this point, for all $k \in [1, K]$, the $k$th UE needs to transmit a reference signal to the APs. Assuming that the DC-biased pulse-amplitude modulation (PAM) with order $C$ is used, the $k$th UE broadcasts through its IR-LED a scalar signal $s_k = I_{DC}$, where $I_{DC}$ denotes the direct-current (DC) intensity bias of the IR-LED. Hence, for all $k \in [1, K]$ and $i \in [1, M]$, the received signal of the $k$th UE at the $i$th AP is given by $z_{k,i} = \lambda_u g_{k,i}(j) s_k + \omega_i$, where $\lambda_u = R_u \eta_u$, in which $R_u$ (A/W) is the responsivity of the PD of the $i$th AP and $\eta_u$ (W/A) is the current-to-power conversion efficiency of the UE’s IR-LED, $g_{k,i}(j)$ is the total uplink channel gain between the $k$th UE and the $i$th AP at time slot $j$, whose expression is given in appendix A and $\omega_i$ is an AWGN experienced at the $i$th AP that is $\mathcal{N}(0, \sigma^2_u)$ distributed, such that $\sigma^2_u = \frac{N_0 B}{K}$.

Based on the above, for all $k \in [1, K]$ and $i \in [1, M]$, the received SNR of the $k$th UE at the $i$th AP at each time slot $j \in [t - N + 1, t]$ is expressed as

$$r_{k,i}(j) = \frac{\lambda^2_u g^2_{k,i}(j) I^2_{DC}}{\sigma^2_u}. \tag{3}$$

Based on this, for all $k \in [1, K]$, the $1 \times M$ received SNR vector of the $k$th UE at the APs at each time slot $j \in [t - N + 1, t]$ is expressed as

$$\mathbf{R}_{\gamma_k}(t) = \begin{bmatrix} \cos \gamma_k(t) & 0 & \sin \gamma_k(t) \\ 0 & 1 & 0 \end{bmatrix}.$$

\begin{align}
R_{\alpha_k}(t) & = \begin{bmatrix} \cos \alpha_k(t) & -\sin \alpha_k(t) & 0 \\
\sin \alpha_k(t) & \cos \alpha_k(t) & 0 \end{bmatrix}, \\
R_{\beta_k}(t) & = \begin{bmatrix} 1 & 0 & 0 \\
0 & \cos \beta_k(t) & -\sin \beta_k(t) \\
0 & \sin \beta_k(t) & \cos \beta_k(t) \end{bmatrix}, \\
R_{\gamma_k}(t) & = \begin{bmatrix} \cos \gamma_k(t) & 0 & \sin \gamma_k(t) \\
0 & 1 & 0 \\
-\sin \gamma_k(t) & 0 & \cos \gamma_k(t) \end{bmatrix}. \tag{2}
\end{align}
which depends mainly on the instantaneous 3D position and orientation vector of the kth UE \( \mathbf{p}_k(t) \) at time slot \( t \). Consequently, as shown in Fig. 3 with the time interval \( [t - N + 1, t] \) and for all \( k \in [1, K] \), the APs collect a group of \( N \) SNR vectors for the kth UE that is expressed as
\[
\mathbf{r}_{k,\text{total}}(t) = [\mathbf{r}_k(t - N + 1), \mathbf{r}_k(t - N + 2), \ldots, \mathbf{r}_k(t)].
\]

C. Prediction Phase

In this phase, the goal is to predict, at each time slot \( t \), the posterior 3D position and orientation vector \( \mathbf{p}_k(t + L) \) of the kth UE relative to time slot \( t + L \), based on its prior RSS values collected between the time slots \( t - N + 1 \) and \( t \). Specifically, as shown in Fig. 3 for all \( k \in [1, K] \), the goal is to predict, at each time slot \( t \), the posterior 3D position and orientation vector \( \mathbf{p}_k(t + L) \) of the kth UE, based on its associated vector of RSS values \( \mathbf{r}_{k,\text{total}}(t) \) collected between time slots \( t - N + 1 \) and \( t \).

As was mentioned in the RSS collection phase in subsection III-B, for all \( k \in [1, K] \), the vector of RSS values \( \mathbf{r}_{k,\text{total}}(t) \) collected between time slots \( t - N + 1 \) and \( t \) is a function of the instantaneous 3D position orientation vector \( \mathbf{p}_k(t) \) of the kth UE at each time slot \( j \in [t - N + 1, t] \), i.e., there exists a deterministic vector-valued function \( \mathbf{F}(\cdot) \) such that
\[
\mathbf{p}_k(t) = \mathbf{F}(\mathbf{r}_k(t)).
\]

In other words, at each time slot \( t \) and for all \( k \in [1, K] \), the vector of total RSS values \( \mathbf{r}_{k,\text{total}}(t) \) collected between the time slots \( t - N + 1 \) and \( t \) contains information about the previous realizations of the 3D position and orientation of the kth UE within the time interval \( [t - N + 1, t] \).

For all \( k \in [1, K] \), since the kth UE is mobile, then its instantaneous 3D position and orientation vector \( \mathbf{p}_k(t) \) is a multivariate random process (RP). In this case, for all \( k \in [1, K] \) and for every time slot \( t \), there exists a probabilistic vector-valued function \( \mathbf{G}(\cdot) \), such that
\[
\begin{bmatrix}
\mathbf{p}_k(t + L) \\
\mathbf{p}_k(t + L - 1) \\
\vdots \\
\mathbf{p}_k(t)
\end{bmatrix} = \mathbf{G}\left(\begin{bmatrix}
\mathbf{p}_k(t) \\
\mathbf{p}_k(t - 1) \\
\vdots \\
\mathbf{p}_k(t - N + 1)
\end{bmatrix}\right).
\]

Consequently, based on (6) and (7), there exists a probabilistic vector-valued function \( \mathbf{J}(\cdot) \), such that, for all \( k \in [1, K] \) and for every time slot \( t \),
\[
\begin{bmatrix}
\mathbf{p}_k(t + L) \\
\mathbf{p}_k(t + L - 1) \\
\vdots \\
\mathbf{p}_k(t)
\end{bmatrix} = \mathbf{J}\left(\begin{bmatrix}
\mathbf{r}_k(t) \\
\mathbf{r}_k(t - 1) \\
\vdots \\
\mathbf{r}_k(t - N + 1)
\end{bmatrix}\right).
\]

Based on (8), the objective here is to determine the probabilistic vector-valued function \( \mathbf{J}(\cdot) \). However, obtaining its exact characterization is not straightforward. In fact, for all \( k \in [1, K] \) and for every time slot \( j \in [t - N + 1, t] \), the vector of RSS values \( \mathbf{r}_k(j) \) includes the contributions of both the LOS and the NLOS components of the wireless links between the kth UE and the M APs. Although the contributions of the NLOS components will improve the prediction accuracy, like it was shown in the estimation problem invoked [19], their inclusion in the prediction process is not straightforward from an optimization point of view, like the case of maximizing an observed predictive likelihood function. This is basically due to their complex expressions as shown in Appendix A.

To overcome this issue, an approximate parametric vector-valued function \( \mathbf{J}(\mathcal{W}_t) \) will be constructed using an artificial neural network (ANN), where \( \mathcal{W} \) is the set of parameters of the ANN. In this case, for all \( k \in [1, K] \) and at each time slot \( t \), the predicted values of the posterior 3D position and orientation of the kth UE relative to time slot \( t + L \) can be obtained as
\[
\begin{bmatrix}
\hat{\mathbf{p}}_k(t + L) \\
\hat{\mathbf{p}}_k(t + L - 1) \\
\vdots \\
\hat{\mathbf{p}}_k(t)
\end{bmatrix} = \mathbf{J}(\mathcal{W}_t, \begin{bmatrix}
\mathbf{r}_k(t) \\
\mathbf{r}_k(t - 1) \\
\vdots \\
\mathbf{r}_k(t - N + 1)
\end{bmatrix}).
\]

The details on how the approximate parametric vector-valued function \( \mathbf{J} \) and the optimal set of parameters \( \mathcal{W}_t^* \) are obtained will be presented in section IV.

Based on the above, for all \( k \in [1, K] \), the predicted 3D position and orientation vector \( \hat{\mathbf{p}}_k(t + L) \) of the kth UE associated to time slot \( t + L \) is obtained and its associated predicted \( M \times 1 \) channel gain vector \( \hat{\mathbf{h}}_k(t + L) \) can be calculated at time slot \( t \). Consequently, the predicted \( K \times M \) channel matrix \( \hat{\mathbf{H}}(t + L) = \begin{bmatrix}
\hat{\mathbf{h}}_1(t + L) & \hat{\mathbf{h}}_2(t + L) & \cdots & \hat{\mathbf{h}}_K(t + L)
\end{bmatrix}^T \) can be obtained at time slot \( t \).

D. Optimization Phase

In this phase, once the predicted \( K \times M \) channel matrix \( \hat{\mathbf{H}}(t + L) \) is obtained, the optimization problem \( \mathcal{P} \left( \hat{\mathbf{H}}(t + L) \right) \) is solved within the time interval \([t, t + L]\). In this case, a sub-optimal solution is obtained and can be employed in serving the cellular users at time slot \( t + L \), without any processing delay at time slot \( t + L \), which overcomes the problem of channel aging of the considered LiFi system that was raised in subsection II-C.

IV. JOINT PREDICTION OF INDOOR LIFI USER POSITION AND ORIENTATION

A. Methodology

In this section, and as discussed in subsection III-C, our objective is to determine an approximate parametric vector-valued function \( \mathbf{J} \) along with its optimal set of parameters \( \mathcal{W}_t^* \) that can predict the posterior 3D position and orientation of the LiFi UEs with a good accuracy. To reach this goal, DL techniques, through the use of ANNs, are employed for this task. DL is a particular machine learning technique that implements the learning process elaborating the data through ANNs. The use of ANNs is a key factor that makes DL outperform other machine learning schemes, especially when a large amount of data is available [34]. This has made DL the leading ML technique in many scientific fields such as image classification, text recognition, speech recognition,
audio and language processing and robotics [34]. The potential application of DL to physical layer communications has also been increasingly recognized because of the new features for future communications, such as complex scenarios with unknown channel models, high speed and accurate processing requirements, which present big challenges to 6G wireless networks [35]. Motivated by this, DL has been applied to wireless communications, such as physical layer communications [35], [36], resource allocation [37], [38], and intelligent traffic control [39]. Motivated by the above discussion, DL techniques are auspicious candidates for the prediction of posterior 3D position and orientation of the LiFi UEs, which is the focus of this section.

The proposed prediction technique consists of two phases: 1) an offline learning (offline phase) and 2) an online deployment (online phase). In the offline learning, a dataset of \( Q \) random sequences, each of length \( N + L_{\text{max}} \), are generated, where \( L_{\text{max}} \) denotes the maximum posterior time slot index. Specifically, for all \( q \in [1, Q] \), a random trajectory of length \( N + L_{\text{max}} \) steps is generated using a predefined experimental-based indoor mobility model, within which a random 3D experimental-based orientation is generated at each step. For all \( q \in [1, Q] \), the process of generating the \( q \)th data point of the dataset is as follows.

1) A sequence \( \{\mathbf{p}^q_1, \mathbf{p}^q_2, ..., \mathbf{p}^q_{N+L_{\text{max}}}\} \) of \( N + L_{\text{max}} \) 3D position and orientation vectors is randomly generated using the experimental-based indoor ORWP [26], where for all \( n \in [1, N + L_{\text{max}}] \), \( \mathbf{p}^q_n \) is the 3D position and orientation vector of the \( q \)th time step of the \( q \)th sequence. The details of the experimental-based ORWP model employed here are presented in Appendix B. Then, the obtained sequence is recorded.

2) For all \( n \in [1, N] \), the \( 1 \times M \) SNR vector \( \mathbf{r}^q_n \) is calculated based on the 3D position and orientation vector \( \mathbf{p}^q_n \).

3) The features vector of the \( q \)th data point is the \( 1 \times N \) sequence of SNR vectors \( \{\mathbf{r}^q_1, \mathbf{r}^q_2, ..., \mathbf{r}^q_N\} \).

4) The labels vector of the \( q \)th data point is the \( 1 \times L \) sequence of posterior 3D position and orientation vector \( \{\mathbf{p}^{q+1}_{N+1}, \mathbf{p}^{q+1}_{N+2}, ..., \mathbf{p}^{q+1}_{N+L_{\text{max}}}\} \).

The structure of the data set is shown in Fig. 4. Afterwards, based on the obtained dataset, optimal ANN models that provide the best approximate parametric vector-valued function \( \hat{f}^q \) that can map between the received SNR vectors and the posterior 3D position and the orientation vectors are designed. Finally, in the online testing, the obtained approximate parametric vector-valued function \( \hat{f} \) is deployed. In the following, we will present first the steps of the offline phase and then we will discuss the deployment of the obtained learning models in the online phase.

### B. Prediction Model

The problem at hand is the prediction of future 3D positions and orientations of a LiFi UE based on its prior received SNR values. Since both the position and the orientation of the UE can be modeled as RPs, as discussed in the previous paragraph, the problem can be formulated as a sequence-to-sequence (Seq2Seq) prediction problem [40], [41]. Seq2Seq prediction is basically a process of extracting useful information from historical records and then determining future values. Unlike regression predictive modeling, Seq2Seq mapping adds the complexity of sequences dependencies among the input variables [40], [41]. A powerful type of neural network designed to handle sequences dependencies is called recurrent neural networks (RNNs). The LSTM network is a category of RNN that is trained using Backpropagation through time and that is known of their capability in alleviating the vanishing gradient problem [42]. As such, LSTM network can be used to create large RNNs that can be used to address difficult Seq2Seq prediction problems. Motivated by this discussion, the approximate parametric vector-valued function \( \hat{f}^q \) is an LSTM network that is trained in the offline phase using the generated dataset. Hence, its optimal set of parameters \( \mathcal{W}^* \) can be obtained that provide the best prediction accuracy can be obtained.

### C. Online Phase

In the online phase, once the LSTM model is optimized, the obtained parametric vector-valued function \( \hat{f}^q(\mathcal{W}^*, \cdot) \) is deployed at the APs. Consequently, for all \( k \in [1, K] \) and at each time slot \( t \), the APs track if there is any change in the received SNR values \( \{r_k(t - N + 1), r_k(t - N + 2), ..., r_k(t)\} \) from the \( k \)th UE within the interval of time \([t-N+1, t]\). If this is the case, the received SNR values are fed into the obtained parametric vector-valued function \( \hat{f}^q(\mathcal{W}^*, \cdot) \) in order to output the sequence of predicted posterior 3D position and orientation vectors of the \( k \)th UE \( \{\hat{\mathbf{p}}_k(t), \hat{\mathbf{p}}_k(t + 1), ..., \hat{\mathbf{p}}_k(t + L)\} \), where \( L \in [1, L_{\text{max}}] \) is the target posterior time slot index. Consequently, the obtained sequences of predicted posterior 3D positions and orientations vectors are injected into the channel matrix expression in order to predict the channel matrix of all UEs associated to time slot \( t + L \), i.e., \( \mathbf{H}(t + L) \). Finally, assuming a certain transmission strategy and a predefined performance metric, the associated optimization problem \( \mathcal{P} \) \( \mathcal{P} \) is solved within the time interval \([t, t + L]\). In this case, a sub-optimal solution is obtained and can be employed in serving the cellular users at time slot \( t + L \) directly, without any processing delay at time slot \( t + L \).
V. APPLICATION: PROACTIVE SUM-RATE MAXIMISATION
OF MULTI-USER CELL-FREE LiFi SYSTEMS

A. Motivation

The main motivation behind predicting the future channel realizations of mobile UEs is to proactively design near-optimal transmission schemes prior to the target service time slot, which will enable real-time near-optimal service for mobile UEs. As an application for the proposed PO technique, a typical optimization problem is considered, which is the sum-rate maximisation of multi-user cell-free LiFi systems with QoS constraints.

B. Signal Model and Rate Analysis

Consider the same indoor LiFi system presented in section II, where at each time slot $t$, the LiFi controller attempts to transmit the vector of messages $u(t) = [u_1(t), u_2(t), ..., u_K(t)]^T$, in which for all $k \in [1, K]$, $u_k(t)$ denotes the message intended to the $k$th UE at time slot $t$. Hence, in order to broadcast these messages through the $M$ APs, the controller multiplexes the messages of the UEs using linear precoding. Based on this, the $M \times 1$ vector of signals $s(t)$ broadcast by the $M$ APs at each time slot $t$ can be expressed as

$$s(t) = V(t)u(t) = \sum_{k=1}^{K} v_k(t)u_k(t), \quad (10)$$

where for all $k \in [1, K]$, $v_k(t)$ presents the $M \times 1$ precoding vector of the $k$th UE at time slot $t$ and $V(t) = [w_1(t), w_2(t), ..., w_K(t)]$ presents the $N \times K$ precoding matrix at time slot $t$.

Typical LEDs suffer from nonlinear distortion and clipping effects, which imposes some operating constraints on the emitted optical power. Precisely, the electrical to optical transfer characteristic of LEDs leads to a unique optical power constraint imposed on the transmitted electrical signals $[6]$. Such constraint ensures the linear input-output operation of the LEDs. Based on $[6]$, the transmitted signal $s$ should satisfy a peak-power constraint, i.e., an amplitude constraint, that is expressed as

$$\|s(t)\|_\infty \leq A, \quad (11)$$

where $A > 0$ represents the maximum allowed signal amplitude at the input of each AP. At this stage, in order to satisfy the peak-power constraint $[11]$, we impose the following constraints on the vectors of messages $u(t)$ and the precoding matrix $V(t)$.

$$\|u(t)\|_\infty \leq A, \quad (12a)$$

$$\|V(t)\|_\infty \leq 1. \quad (12b)$$

Consequently, for all $k \in [1, K]$, the received signal at the $k$th UE at each time slot $t$ is expressed as

$$y_k(t) = h_k^T(t)V(t)u(t) + n_k(t),$$

$$\quad = h_k^T(t)v_k(t)u_k(t) + h_k^T(t)V_k(t)u_k(t) + n_k(t), \quad (13)$$

where $V_k(t)$ is the $N \times (K-1)$ matrix that is equal to the precoding matrix $V(t)$ after removing the $k$th column and $u_k(t)$ is the $K-1$ vector that is equal to the vector of messages $u(t)$ after removing the $k$th element.

As depicted in the received signal’s expression in $[13]$, each UE suffers from an inter-user interference, which is due to the transmission of the messages of all UEs within the same time/frequency resource block. One solution to cancel the effects of the inter-user interference at each UE is to force this interference to be equal to zero at its reception. This cancellation can occur by imposing the following constraints

$$h_k^T(t)v_i(t) = 0, \quad \forall (k, i) \in \{1, K\}^2 \& i \neq k, \quad (14)$$

or equivalently,

$$H(t)V(t) = \text{diagonal matrix}, \quad (15)$$

where $H(t) = [h_1(t), h_2(t), ..., h_K(t)]^T$ denotes the channel matrix of the considered multi-user LiFi system. Based on this description and the results of $[43]$, for all $k \in [1, K]$ the instantaneous achievable rate at the $k$th UE at each time slot $t$ can be expressed as

$$R_k(h_k(t), v_k(t)) = \frac{1}{2} \log \left(1 + \frac{cA^2(h_k(t)^TV_k(t))^2}{2\pi e\sigma^2}\right). \quad (16)$$

C. Problem Formulation

With the objective of maximizing the instantaneous achievable sum-rate of the considered LiFi system while guaranteeing a target QoS for each UE, an optimal design of the instantaneous precoding matrix $V(t)$ can be obtained through the following optimization problem.

$$\mathcal{P}[H(t)] : \max_{V(t)} \sum_{k=1}^{K} R_k(h_k(t), v_k(t))$$

s.t. $h_k^T(t)v_i(t) = 0,$

$$\forall (k, i) \in \{1, K\}^2 \& i \neq k, \quad (17b)$$

$$R_k \leq R_k(h_k(t), v_k(t)), \forall k \in \{1, K\}, \quad (17c)$$

$$\|V(t)\|_\infty \leq 1. \quad (17d)$$

Problem $\mathcal{P}[H(t)]$ is a non-linear non-convex problem and, thus, obtaining its optimal solution is not straightforward. Some heuristic approaches can be employed to obtain sub-optimal solutions for problem $\mathcal{P}[H(t)]$. However, these approaches require a processing time that may exceed the maximum amount of time allocated to serve the different users, which raises the channel aging problem invoked in this paper. To overcome this issue, the proposed PO approach can be applied. Consequently, considering a posterior time slot index $L$, we are interested in solving at each time slot
the optimization problem \( P \left[ \mathbf{H}(t + L) \right] \) is expressed as follows.

\[
P \left[ \mathbf{H}(t + L) \right] : \max_{\mathbf{V}(t+L)} \sum_{k=1}^{K} R_k \left( \mathbf{h}_k(t + L), \mathbf{v}_k(t + L) \right)
\]

\[
\text{s.t. } \mathbf{h}_k(t + L)\mathbf{v}_k(t + L) = 0, \quad \forall (k, i) \in \{1, K\}^2 \& i \neq k,
\]

\[
R_{th} \leq R_k \left( \mathbf{h}_k(t + L), \mathbf{v}_k(t + L) \right), \quad \forall k \in \{1, K\},
\]

\[
||\mathbf{V}(t + L)||_{\infty} \leq 1.
\]

\[ \boxed{(18a)} \]
\[ \boxed{(18b)} \]
\[ \boxed{(18c)} \]
\[ \boxed{(18d)} \]

Solving problem \( P \left[ \mathbf{H}(t + L) \right] \) is operated within the time interval \([t, t + L]\) which enables obtaining the optimal precoding matrix \( \mathbf{V}^*(t + L) \) prior to the service time slot \( t + L \).

Problem \( P \left[ \mathbf{H}(t + L) \right] \) is also a non-linear non-convex problem and, thus, obtaining its optimal solution is not straightforward. Alternatively, we propose in the following a solution approach that can reach a near-optimal solution. Consider the change of variable given by

\[
\mathbf{V}(t + L) = \mathbf{H}(t + L)^{-1} \mathbf{X},
\]

\[ \boxed{(19)} \]

where \((\cdot)^{-1}\) denotes the pseudo-inverse operator and \( \mathbf{X} = \text{diag}(\mathbf{x}) \) is a \( K \times K \) diagonal matrix, such that \( \mathbf{x} = [x_1, x_2, \ldots, x_K]^T \) is a \( K \times 1 \) real vector. Based on this, constraint \( (18b) \) is satisfied and problem \( P \left[ \mathbf{H}(t + L) \right] \) can be re-expressed as

\[
P'' \left[ \mathbf{H}(t + L) \right] : -\min_{\mathbf{x}} \sum_{k=1}^{K} -\frac{1}{2} \log \left( 1 + \rho x_k^2(t) \right), \quad \boxed{(20a)}
\]

\[
\text{s.t. } R_{th} - \frac{1}{2} \log \left( 1 + \rho x_k^2 \right) \leq 0, \quad \forall k \in \{1, K\},
\]

\[
\left| \mathbf{H}(t + L)^{-1} \text{diag}(\mathbf{x}(t)) \right|_{\infty} \leq 1.
\]

\[ \boxed{(20b)} \]
\[ \boxed{(20c)} \]

The function \( x \rightarrow f(x) = -\frac{1}{2} \log \left( 1 + \rho x^2 \right) \) is a smooth function and its second derivative is expressed as

\[
\frac{\partial^2 f(x)}{\partial x^2} = \frac{\rho \rho x^2 - 1}{\left( \rho x^2 + 1 \right)^2}, \quad \boxed{(21)}
\]

which is positive if \( x^2 \geq \frac{1}{\rho} \) and negative otherwise. Hence, the function \( f \) is convex if \( x^2 \geq \frac{1}{\rho} \) and concave otherwise.

Consequently, problem \( P'' \left[ \mathbf{H}(t + L) \right] \) is not convex. To deal with this issue, we convexify problem \( P'' \left[ \mathbf{H}(t + L) \right] \) by employing the CCP proposed in [44]. Using CCP, and based on the description in [44], the objective function \( (20a) \) and the constraints in \( (20b) \) are convexified by linearizing them around a certain point \( \mathbf{y}_j = [y_{j,1}, y_{j,2}, \ldots, y_{j,K}]^T \) through the first order Taylor approximation. In this case, the convex form of problem \( P'' \left[ \mathbf{H}(t + L) \right] \) is given by \( (22) \) on top of next page.

**Algorithm 1** Iterative algorithm for solving \( P \left[ \mathbf{H}(t + L) \right] \)

1. **Initialization**: Choose an initial feasible point \( \mathbf{y}_0 \).
2. **Set**: \( j = 0 \).
3. **Repeat**: \( j \rightarrow j + 1 \).
   i. Update iteration \( j \rightarrow j + 1 \).
   ii. Solve \( P'' \left[ \mathbf{H}(t + L), \mathbf{y}_{j} \right] \).
   iii. Assign the solution to \( \mathbf{y}_{j+1} \).
4. **Termination**: terminate step 3. when
   i. \( |g(\mathbf{x}, \mathbf{y}_{j-1}) - g(\mathbf{x}, \mathbf{y}_{j})| \leq \epsilon \), or
   ii. \( j = j_{\text{max}} \).
5. **Assign**: \( \mathbf{x}^* = \mathbf{x}_j \).
6. **Construct**: \( \mathbf{V}^*(t + L) = \mathbf{H}(t + L)^{-1} \text{diag}(\mathbf{x}^*) \).

Problem \( P'' \left[ \mathbf{H}(t + L), \mathbf{y}_j \right] \) is a convex optimization problem that depends on the linearization point \( \mathbf{y}_j \) and can be solved efficiently using standard optimization packages [45], [46]. The detailed iterative algorithm for solving the original problem \( P \left[ \mathbf{H}(t + L) \right] \) is given in Algorithm 1, where the initial point \( \mathbf{y}_1 \) is a random feasible point that satisfies the constraints of problem \( P \left[ \mathbf{H}(t + L) \right] \). \( g(\cdot, \cdot) \) is the objective function in \( (22a) \) of problem \( P'' \left[ \mathbf{H}(t + L), \mathbf{y}_j \right] \), \( \epsilon \) is a gap threshold and \( j_{\text{max}} \) is a maximum number of iterations. Finally, once the precoding matrix \( \mathbf{V}^*(t) \) is obtained, it is applied directly at time slot \( t + L \).

**VI. SIMULATION RESULTS**

In this section, our objective is to evaluate the performance of the proposed PO approach through extensive simulations.

**A. Simulations Parameters**

In this paper, we consider a typical indoor environment with dimensions \( L \times W \times H = 10 \times 10 \times 3 \) m\(^3\). The indoor environment is equipped with \( M = 16 \) APs which are arranged on the vertices of a square lattice over the ceiling of the room, where each AP is oriented vertically downward. In addition, a LiFi UE, that is equipped with one IR-LED and one PD, is randomly located within the room and its UE may have a random orientation. The UE is a typical smartphone with dimensions \( 14 \times 7 \times 1 \) cm\(^3\). The IR-LED and the PD are adjacent to each other and are placed at screen of the smartphone, exactly at 6 cm above the center. The parameters used throughout the paper are shown in Table III.

The central processing unit (CPU) of the machine on which all the simulations were performed was an Intel Core i5 from the second generation that has a dual-core, a basic frequency of 2.40 GHz and a maximum turbo frequency of 3.40 GHz.

**B. Artificial Neural Networks Specifications**

The architecture of the LSTM model is shown in Table III. For comparison purposes, a CNN model is considered. The
\[
P''[\mathbf{H}(t+L), y_j] : \quad \min_{\mathbf{H}} \sum_{k=1}^{K} \left( -\frac{1}{2} \log \left( 1 + \rho y_{j,k}^2 \right) - \frac{\rho y_{j,k}}{y_{j,k}^2 + 1} \times (x_k(t) - y_{j,k}) \right),
\]
\[
s.t. \quad R_{th} - \frac{1}{2} \log \left( 1 + \rho y_{j,k}^2 \right) - \frac{\rho y_{j,k}}{y_{j,k}^2 + 1} \times (x_k(t) - y_{j,k}) \leq 0, \quad \forall \ k \in [1, K],
\]
\[
||\mathbf{H}(t)\operatorname{diag}(\mathbf{x}(t))||_\infty \leq 1.
\]

### TABLE II: Simulation Parameters

| Parameter                  | Symbol | Value |
|----------------------------|--------|-------|
| Room dimension             | \(L \times W \times H\) | 5m \(\times\) 5m \(\times\) 3m |
| Mean UE’s height           | 2      | 1.4m  |
| UE’s height standard deviation | \(\sigma_z\) | 0.05  |
| User indoor walking speed  | \(v\)  | 1 m/second |
| Time slot duration         | \(\delta t\) | 0.5 second |
| PD responsivity           | \(R_{1d}, R_{2u}\) | 0.6 A/W |
| Current-to-power conversion factor | \(\eta_{1d}, \eta_{2u}\) | 0.8 W/A |
| LED half-power semicircle | \(\Phi_{1/2}\) | 60\(^\circ\) |
| PD geometric area          | \(\Lambda_p\) | 1 cm\(^2\) |
| Optical concentrator refractive index | \(n_c\) | 1 |
| Reflection coefficient of the walls | \(\rho\) | 0.7 |
| Field of view of the LED   | \(\Phi\) | 90\(^\circ\) |
| Field of view of the PD    | \(\Psi\) | 90\(^\circ\) |
| System Bandwidth           | \(B\)  | 10 MHz |
| Noise power spectral density | \(N_0\) | \(10^{-22}\) W/Hz |

### TABLE III: ANNs Specifications

| Prior time slot index | \(N = 8\) |
|-----------------------|------------|
| Maximum posterior time slot index | \(L_{\text{max}} = 4\) |
| Dataset size | \(Q = 10^6\) |
| (Train, test) partition | \((0.9, 0.1) \times Q\) |
| Number of LSTM units | 100 |
| LSTM activation function | Hyperbolic tangent (tanh) |
| LSTM recurrent activation function | Sigmoid |
| Number of CNN hidden layers | 2 |
| Kernel size for each CNN neuron | 4 |
| CNN hidden layer activation | Relu |
| CNN output layer activation | Linear |
| Total number of parameters | LSTM: 24,224 CNN: 25,848 |
| Optimizer | Adam |

![CNN Neuron architecture](image)

**Fig. 5:** CNN Neuron architecture: (a) in each hidden layer (b) in the output layer.

Design of the considered CNN is optimized and the optimal model consists of an input layer, an output layer and 2 hidden layers, where each hidden layer is composed of 16 filters. In addition, the kernel size of each convolution neuron is composed of 4 parameters. In this CNN model, the structure of each neuron in each hidden layer is presented in Fig. 5. As shown in Fig. 5(a), each neuron consists of a convolution layer, a Relu layer, a dropout layer and a normalization layer. The convolution layer operates the convolution between the input of the neuron and its kernel. Then, the Relu layer applies the Relu activation function to the resulting output from the dense layer. After this, at each training stage, individual neurons are dropped out of the ANN with a certain probability, so that the network is reducing. This layer is fundamental in order to prevent overfitting of the ANNs [47]. Finally, the normalization layer scales the input so that the output has near to a zero mean and unit standard deviation, to allow a faster and a more resilient training. Concerning the neurons architecture at the output layer, and as shown in Fig. 5(b), each one consists of a dense layer and a linear activation layer that establishes a link with each label at the output. The design of the LSTM and CNN models is performed using the programming environment Python 3 and the Keras library developed by Google’s TensorFlow team in 2017 [48]. The required codes for generating the datasets, designing, training and testing the LSTM and CNN models are provided in [49].

### C. Learning and Estimation Performance Evaluation

The required time to generate a data set of size \(Q = 10^6\) data points is approximately 6 hours. In the other hand, the time required to train the designed LSTM and CNN models is 14 mins and 1.5 hours, respectively. Although the time required for the data set generation and the models training is large, this high computational time is not an issue, since the data set generation and the models training is performed in the offline phase and only once prior to the deployment of the APs.

![Training and Validation Loss versus the epoch index](image)

**Fig. 6:** Training and Validation Loss versus the epoch index.
Considering the online complexity, the computational time of the designed LSTM and CNN models in the online phase is extremely low. In fact, over the whole test set, which has a size of $0.1 \times Q = 10^5$, the total prediction time in the online phase is 3 seconds and 6.56 seconds for the LSTM and CNN models respectively. Therefore, the average prediction time per trial is $3/10^5 = 0.03$ millisecond and $6.56/10^5 = 0.07$ millisecond for the LSTM and CNN models respectively, i.e., real-time prediction. In addition, the reported results demonstrate the superiority of the designed LSTM model over the CNN model. This makes the designed LSTM model an auspicious solution for accurate and real-time predictions.

Fig. 6 presents the training and validation losses of the designed LSTM and CNN networks, measured in terms of the mean-squared-error (MSE), versus the training epoch index. As it can be seen from Fig. 6 the training and validation losses decrease as the epoch index increases, which demonstrates that the designed LSTM and CNN networks are both not overfitting and can generalize well over unseen data points in the online phase.

Fig. 7 presents the empirical cumulative distribution function (CDF) of the instantaneous positioning error resulting from the designed LSTM and CNN models for different values of the posterior time slot index $L$. This figure shows that the LSTM model provides higher positioning accuracy than the CNN model. In the same context, as shown in Table IV when the posterior time slot index $L = 1$, the reported average positioning errors are 0.19m and 0.47m for the LSTM and the CNN models, respectively, whereas when $L = 4$, the reported average positioning errors are 0.32m and 0.65m for the LSTM and the CNN models, respectively. On the other hand, Fig. 7 shows that the instantaneous position error increases as the posterior time slot index increases. This result is expected since, as the posterior time slot index $L$ increases, more uncertainty about the future positions will be considered.

Considering the prediction performance for the orientation angles, Fig. 8 presents the empirical CDFs of the prediction error of the orientation angles yaw $\alpha$, pitch $\beta$ and roll $\gamma$. First, the same interpretations established for the positioning error apply for the yaw angle $\alpha$, where its average prediction error fluctuates slightly around its mean. For the pitch angle $\beta$ and the roll angle $\gamma$, the standard deviation of the prediction error is very low, i.e., both $\beta$ and $\gamma$ fluctuates around their means presented in Table IV. However, for the pitch angle $\beta$ and the roll angle $\gamma$, Fig. 8 and Table IV show that the LSTM model and the CNN model exhibit the same prediction performance. In addition, the prediction performance does not change as the posterior time slot index increases. These observations are basically due to the fact that, from the experimental-based statistics presented in Table IV in Appendix B, the standard deviation of the pitch angle $\beta$ and the roll angle $\gamma$ are very low, i.e., both $\beta$ and $\gamma$ fluctuates slightly around their means presented in Appendix B.

D. Sum Rate Performance Evaluation

In this subsection, we consider the proactive sum-rate maximization of the multiuser cell-free LiFi system considered in section V as an application of the proposed PO approach. The results presented within this subsection are obtained from independent Monte-Carlo trials over the whole test set. For a given prior time slot index $L$, and at each time slot $t$, four different cases are considered, which are

1) **Baseline 1**: The exact instantaneous channel matrix $H(t+L)$ is perfectly estimated at time slot $t+L$ and then the corresponding optimal precoding matrix is obtained at the same time slot without considering any processing delay.

2) **Proposed PO**: The predicted instantaneous channel matrix $\hat{H}(t+L)$ is obtained from the optimized LSTM model at time slot $t$ and then the corresponding optimal precoding matrix is obtained within the time interval $[t,t+L]$.

3) **Baseline 2**: The predicted instantaneous channel matrix $\hat{H}(t+L)$ is obtained from the optimized CNN model at time slot $t$ and then the corresponding optimal precoding matrix is obtained within the time interval $[t,t+L]$.

4) **Baseline 3**: The exact instantaneous channel matrix $H(t)$ is perfectly estimated at time slot $t$. Then the corresponding optimal precoding matrix is obtained within the time interval $[t,t+L]$ and then applied at time slot $t+L$.

**Baseline 1** is considered in this section as an upper bound to assess the performance of **Proposed PO** scheme, since at each time slot $t+L$, the idealistic scenario is to obtain the corresponding optimal precoding matrix at the same time slot without any processing delay. Moreover, **Baseline 3** is considered here to demonstrate the performance degradation caused by the channel aging problem invoked in this paper, since the precoding matrix associated to the instantaneous channel matrix $H(t)$ is obtained within the time interval $[t,t+L]$, and therefore, applied for the instantaneous channel matrix $H(t+L)$. On the other hand, for each case discussed above, the associated precoding matrix is obtained using two approaches, which are

- The optimal approach that consists of running an off-the-shelf optimization solver\(^1\).
- The CCP approach (**Algorithm 1**).

\(^1\)The adopted solver is fmincon, which is a predefined matlab solver. In addition, 10 distinct initial points were generated in order to converge to the optimal solution.
TABLE IV: Average prediction error of the position and the orientation angles yaw $\alpha$, pitch $\beta$ and roll $\gamma$.

| L | LSTM | CNN | LSTM | CNN | LSTM | CNN | LSTM | CNN |
|---|------|-----|------|-----|------|-----|------|-----|
| Position | 0.1789 m | 0.4742 m | 0.2136 m | 0.5192 m | 0.2565 m | 0.5750 m | 0.3046 m | 0.6385 m |
| Yaw angle $\alpha$ | 22.4266° | 32.6992° | 22.8108° | 32.4743° | 22.8551° | 32.5409° | 22.4539° | 32.4700° |
| Pitch angle $\beta$ | 2.5974° | 2.6003° | 2.6013° | 2.6068° | 2.5985° | 2.5991° | 2.6003° | 2.6063° |
| Roll angle $\gamma$ | 4.3254° | 4.3202° | 4.3212° | 4.3338° | 4.3114° | 4.3101° | 4.3406° | 4.3381° |

In line with the above, Fig. 8 presents the average sum rate of the considered cell-free LiFi system versus the number of LiFi UEs $K$ for the different cases presented above, where the posterior time slot index $L = 2$ and the required rate threshold per UE is $R_{th} = 2$ nats/s/Hz. Fig. 9 demonstrates that the CCP approaches provides a near-optimal solution for the problem in hand, where the gap between average sum rate obtained from using the optimal solution and the CCP solution is less than $0.01\%$ for all the considered scenarios. On the other hand, by comparing Baseline 3 to Baseline 1, Fig. 9 shows the performance degradation that is caused by the channel aging problem, where the highest gap between the average sum rates associated to Baseline 1 and Baseline 3 is higher than $20\%$ for the considered range of number of UEs. However, the proposed PO approach outperforms Baseline 3 and brings a performance enhancement to the system, where the highest gap between the average sum rates associated to Baseline 1 and the proposed PO is less than $7\%$. On the other hand, and in accordance with the results obtained in the previous subsection, Fig. 9 shows that the LSTM model outperforms the CNN model, since the highest gap between the average sum rates associated Baseline 1 and Baseline 2 is higher than $10\%$.

Fig. 10 presents the average sum rate of the considered cell-free LiFi system versus the number of LiFi UEs $K = 4$ and the posterior time slot index $L = 2$. In addition, this figure shows that the sum rate of the system decreases as the rate threshold $R_{th}$ increases. This is basically expected, since when the rate threshold $R_{th}$ increases, the number of users that are admitted to the networks increases, and this is due to the fact that their channel realizations can
not satisfy the target QoS.

Fig. 11 presents the average computational time of the optimal optimization approach and the CCP approach for obtaining the best precoding matrix $V$ for the considered LiFi system versus the number of LiFi UEs. This figure shows that the computational time increases as the number of UEs increases, which is expected, since as the number of UEs increases, the number of optimization variables increases. In addition, this figure demonstrates that the CCP approach has a lower computational time than the one of the optimal optimization approach (at least 50% less). In addition, recall that the CCP approach provides a performance gap that is less than 0.01% from the optimal approach. This demonstrates the potential of the CCP approach in providing an optimal solution with a low computational time for the considered problem. Moreover, since the duration of one time slot is 0.5 seconds, the solution of the CCP approach can be obtained within one time slot. Therefore, the proposed PO approach can be applied even for a posterior time slot index $\hat{L} = 1$, i.e., at each time slot $t$, the a near-optimal solution can be provided using the LSTM model and the CCP approach in the time interval $[t, t + 1]$. Therefore, for each time slot $t$, a near optimal precoding matrix $V$ can be applied directly at time slot $t + 1$ without any processing delay.

VII. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

With the objective of overcoming the LiFi channel aging problem, a PO approach for indoor LiFi systems is proposed in this paper. The core of the proposed technique is one LSTM network that is capable of predicting posterior positions and orientations of mobile users following random trajectories in indoor environments. Afterwards, these predicted posterior positions and orientations are used to predict the channel coefficients of mobile wireless links. Finally, the obtained predicted channel coefficients are exploited for deriving near-optimal power allocation schemes prior to the intended service time, which enables optimal and real-time service for mobile LiFi users. Through various simulations, the of the proposed PO approach is investigated in a typical optimization problem, which is the sum rate maximization of multiuser cell-free LiFi systems with quality-of-service (QoS) constraints. For this case, a performance gap of less than 7% is achieved, while saving up to 100% in the computational time. This demonstrates the potential of the proposed PO approach in providing near-optimal and real-time service of mobile LiFi users and in alleviating the LiFi channel aging problem.

APPENDIX A

LiFi CHANNEL MODEL

In this section, the objective is to explain the LiFi channel model adopted in this paper. For all $i \in [1, M]$ and $k \in [1, K]$, Fig. 12 presents the link geometry between the $i$th AP and the PD of the $k$th UE. Based on this figure, and for all $i \in [1, M]$ and $k \in [1, K]$, the downlink channel gain of the wireless link between the $i$th AP and the PD of the $k$th UE is expressed as [19], [26]

$$h_{k,i} = h_{k,i}^{\text{LOS}} + h_{k,i}^{\text{NLOS}},$$

such that $h_{k,i}^{\text{LOS}}$ and $h_{k,i}^{\text{NLOS}}$ denote the LOS and the NLOS channel gains of this link, respectively. Both the LOS and the NLOS components depend on the positions of the corresponding AP as well as the position and orientation of the corresponding PD or the UE, which is explained as follows. Based on this, for all $k \in [1, K]$ and $i \in [1, M]$, the LOS channel gain $h_{k,i}^{\text{LOS}}$ is expressed as [51]

$$h_{k,i}^{\text{LOS}} = \frac{(m + 1) A_{P}}{2 \pi d_{k,i}^{2}} \cos^m (\phi_{k,i}) \text{rect} \left( \frac{\phi_{k,i}}{\Phi} \right) \times \cos (\psi_{k,i}) \text{rect} \left( \frac{\psi_{k,i}}{\Psi} \right),$$

where $m = -1/\log_2(\cos(\Phi/2))$ is the Lambertian emission order of the AP’s LED, such that $\Phi/2$ is the associated half-power semi-angle, $A_{P} = \pi r_c^2 A_{k}$ is the effective area of the PD of the $k$th UE, such that $r_c$ is the refractive index of the PD’s optical concentrator and $A_{k}$ is the geometric area of the PD, $\phi_{k,i}$ is the radiance angle, $\Phi$ is the field-of-view (FOV) of the AP’s LED, $\psi_{k,i}$ is the incidence angle, $\Psi$ is the FOV of the PD of the UE’s PD and $d_{k,i}$ is the distance between the $i$th AP and the PD of the $k$th PD.

Considering the NLOS components of the LiFi channel gain, they can be calculated based on the method described in [22]. Using the frequency domain instead of the time domain analysis, one is able to consider an infinite number of reflections to have an accurate value of the diffuse link. The environment is segmented into a number of surface elements which reflect the light beams. These surface elements are modeled as Lambertian radiators described by [24] with $m = 1$ and FOV of 90°. Assuming that the entire room can be decomposed into $\xi$ surface elements, the NLOS channel gain $h_{k,i}^{\text{NLOS}}$, including a infinite number of reflections between the LED of the $i$th AP and the PD of the $k$th UE, for all $i \in [1, M]$ and $k \in [1, K]$, can be expressed as $h_{k,i}^{\text{NLOS}} = r^T G_{\xi} (I - EG_{\xi})^{-1} t$, where the vectors $t$ and $r$ respectively represent the LOS link between the LED of the $i$th AP and all the surface elements of the room and from all the surface elements of the room to the PD of the $k$th AP.
PD [52]. The matrix $G_\xi = \text{diag}(\rho_1, ..., \rho_\xi)$ is the reflectivity matrix of all $\xi$ reflectors, $E$ is the LOS transfer function of size $\xi \times \xi$ for the links between all surface elements, and $I_\xi$ is the unity matrix of order $\xi$. The elements of $E$, $r$ and $t$ are found according to (24) and Fig. [12] between the LED of the AP, the surface elements and PD of the UE.

In this context, the RWP can be mathematically defined as a sequence of length $N$ of $\xi$ couples

$$\{b_1, (\Theta_1), (b_2, \Theta_2), ..., (b_{N+L_{\text{max}}}, (\Theta_{N+L_{\text{max}}})\}$$

where for all $n \in [1, N + L_{\text{max}}]$, $\Theta_n = (\alpha(n), \beta(n), \gamma(n))$ is a random vector process describing the UE’s orientation during the movement from waypoint $b_{n-1}$ to waypoint $b_n$. The entities, $\alpha$, $\beta$ and $\gamma$ are RPs. On the other hand, a set of experiments were conducted in [22], where accurate measurements-based statistical models for the orientation angles $(\alpha, \beta, \gamma)$ were derived. Measurements were recorded for mobile users (walking activity), while some users were doing normal activities like browsing or watching a video stream. Based on this, the rotation angles $\alpha$, $\beta$ and $\gamma$, have been shown to follow each a truncated Gaussian distribution with a mean and a standard deviation presented in Table V.

According to the experimental measurements in [22], the adjacent samples of the RPs $\alpha$, $\beta$ and $\gamma$ are correlated. Hence, to incorporate the device orientation with the RWP mobility

\begin{table}[h]
\centering
\caption{Statistics of orientation measurement.}
\begin{tabular}{lccc}
\hline
 & $\alpha$ & $\beta$ & $\gamma$ \\
Mean & 11.90° & 28.81° & -1.35° \\
Standard deviation & 10° & 3.26° & 5.42° \\
\hline
\end{tabular}
\end{table}

The UE’s movement affects its height through the $z$-axis, which encompasses small movements or vibrations in the $z$-direction. Similar to [55], this random motion is modeled as a Gaussian distribution. Hence, for all $n \in [1, N + L_{\text{max}}]$, the UE’s height at the $n$th time step is given by

$$z_n = \bar{z} + N(0, \sigma_z^2),$$

where $\bar{z}$ denotes the mean height that the UE fluctuates around and $\sigma_z$ is the standard deviation.

**APPENDIX B**

**INDOOR MOBILITY AND ORIENTATION MODELS**

**A. Mobility Model**

The main component in generating the dataset is the random trajectory that a LiFi UE follows within the indoor environment. Such trajectory can be generated using a certain realistic mobility model. The random waypoint (RWP) mobility model is one of the most widely used experimental-based mobility models, which is utilized for both experimental and simulation based studies of wireless networks [55]. The RWP mobility model specifies the following characterizations, a) destination points are chosen randomly following a uniform distribution in the indoor environment, and ii) a typical user moves with a constant speed on a straight line between two consecutive waypoints [54]. Such straight line can be divided into several time steps that links the start and the end movement times between the two waypoints. The RWP model is identified as a 2D discrete-time stochastic RP.

Let $\delta t$ [seconds] denotes the amount of time or the duration of one time slot and let $\Omega$ denotes the movement direction of a user while walking, which is measured from the East direction in the Earth coordinate system as shown in Fig. [13]. A recent experimental-based study in [26] demonstrated that the movement direction $\Omega$ is uniformly distributed within $[0, 2\pi]$. In this context, the RWP can be mathematically defined as a sequence of length $N + L_{\text{max}}$ that is $\{b_1, b_2, ..., b_{N+L_{\text{max}}}\}$ where the initial waypoint $b_1 = (x(1), y(1))$ is uniformly distributed within the area of the indoor environment and for all $n \in [1, N + L_{\text{max}}-1]$ the UE moves from $b_n = (x(n), y(n))$ to $b_{n+1} = (x(n+1), y(n+1))$ with a constant speed of $v$, such that

$$b_{n+1} = v \times \delta t \times (\cos(\Omega), \sin(\Omega)) + b_n,$$  

**B. Orientation Model**

In order to provide a more realistic framework for analyzing the performance of mobile wireless networks in LiFi, it is required to combine the conventional RWP with the random orientation model. An ORWP mobility model was introduced in [22], where the elevation angle of the UE is included during the user’s movement. Recently, an altered version of ORWP, where the orientation angles yaw $\alpha$, pitch angle $\beta$ and roll angle $\gamma$ are encompassed, was used in [26] to evaluate the system performance metrics (such as received SNR) more accurately for mobile users. Within the context of this paper, the ORWP can be modeled as a sequence of $N + L_{\text{max}}$ couples defined as $\{(b_1, \Theta_1), (b_2, \Theta_2), ..., (b_{N+L_{\text{max}}}, \Theta_{N+L_{\text{max}}})\}$, where for all $n \in [1, N + L_{\text{max}}]$, $\Theta_n = (\alpha(n), \beta(n), \gamma(n))$ is a random vector process describing the UE’s orientation during the movement from waypoint $b_{n-1}$ to waypoint $b_n$. The entities, $\alpha$, $\beta$ and $\gamma$ are RPs. On the other hand, a set of experiments were conducted in [22], where accurate measurements-based statistical models for the orientation angles $(\alpha, \beta, \gamma)$ were derived. Measurements were recorded for mobile users (walking activity), while some users were doing normal activities like browsing or watching a video stream. Based on this, the rotation angles $\alpha$, $\beta$ and $\gamma$, have been shown to follow each a truncated Gaussian distribution with a mean and a standard deviation presented in Table V.
model, a correlated Gaussian RP which statistically follows the experimental measurements should be generated. In this context, based on the results of [22], the nth time sample of the correlated Gaussian vector process $\Theta_n$ is modeled as a first order linear autoregressive AR(1) filter that is expressed, for all $n \in \mathbb{N}$, as

$$\Theta_n = [\Theta_{n-1} + \epsilon_n] + \sum_{l=1}^{3} c_l \Theta_{n-l},$$

where for all $l \in 1, 2, 3$, $\epsilon_n$ is a white noise random process with variance $\sigma_w^2$, such that

$$\begin{bmatrix} c_1 \\ c_2 \\ c_3 \end{bmatrix} = \begin{bmatrix} 0.05 \delta t_c \alpha \\ 0.05 \delta t_c \beta \\ 0.05 \delta t_c \gamma \end{bmatrix}$$

and

$$\sigma_{w,1}^2 = (1 - c_1)^2 \sigma_x^2,$$

$$\sigma_{w,2}^2 = (1 - c_2)^2 \sigma_y^2,$$

$$\sigma_{w,3}^2 = (1 - c_3)^2 \sigma_z^2,$$

in which $T_{c,\alpha}$, $T_{c,\beta}$ and $T_{c,\gamma}$ denote the coherence times of $\alpha$, $\beta$ and $\gamma$, respectively. Finally, based on the above analysis, for all $n \in [1, N + L_{\text{max}}]$, the 3D position and orientation vector is expressed as $p(n) = [b, z, \theta]$.  

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