Deep Learning Based Proactive Optimization for Mobile LiFi Systems With Channel Aging

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Abstract—This paper investigates the channel aging problem of mobile 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 delay at the physical layer. Hence, the obtained solutions are rendered sub-optimal since the LiFi channels are evolving. In this paper, a proactive-optimization (PO) 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 to derive 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 error and inference complexity, as well as its application in a practical LiFi optimization problem.

Index Terms—LiFi, LSTM, mobile users, prediction, proactive optimization, 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 [2]. The main goals of 6G networks are 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 [3]. Therefore, 6G networks must urgently provide high data rates, seamless connectivity, ubiquitous coverage, and ultra-low latency communications in order to reach the preset targets [3]. Motivated by this, 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 (IR), and the visible light (VL) bands to meet these high requirements [3].

Light-fidelity (LiFi) is a novel bidirectional, high speed, and fully networked optical wireless communication (OWC) technology, that uses VL as the propagation medium in the downlink for the purposes of illumination and wireless communication. It can use IR in the uplink so that the illumination constraint of a room remains unaffected, and also to avoid interference with the VL in the downlink [4]. LiFi offers a number of important benefits that have made it a candidate solution for 6G networks [5]. These include the very large, unregulated bandwidth available in the VL and IR spectra, the high energy efficiency [6], the straightforward deployment that uses off-the-shelf light emitting diode (LED) and photodiode (PD) devices at the transmitter and receiver ends, respectively, and the enhanced security as light does not penetrate through opaque objects [7].

The availability of location and data of mobile terminals at the communications stations, such as access points (APs) and base stations (BSs), and their knowledge by the telecommunications operators has become a key factor in enabling 6G networks [8]. Such information enables better estimation of the quality of the wireless links, which can improve the resource management and provide new location-based services [9]. In indoor applications, various positioning systems that use indoor wireless signals, such as wireless-fidelity (Wi-Fi) [10], Bluetooth [11], radio frequency identification (RFID), mmWave [12], LiFi [13], have been proposed 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 [14].
In addition to the knowledge of the position of a user equipment (UE), the knowledge of UE’s orientation is also a crucial factor, particularly for indoor position-based applications, such as smart factories and smart agriculture [15], [16]. 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 in terms of joint UE position and orientation estimation, since their performance suffers from the limited number of available APs in their local area [17]. 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 it [18].

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 [19]. 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 management tasks [20]. For this purpose, novel and accurate position and orientation estimation solutions were recently proposed in the literature [20], [21], [22]. An inertial measurement unit (IMU) was required in [21] to measure the UE tilt angle for position estimation. In [22], a simultaneous position and orientation (SPO) 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. Recently, artificial intelligence (AI)/machine learning techniques were explored in estimating and predicting the position and the orientation of LiFi UEs, as well as the LiFi channel gains. In particular, in [20], a deep learning (DL) based joint position and orientation estimation technique was proposed. Specifically, two different artificial neural networks (ANNs) were designed and optimized to estimate the 3D position and orientation of a LiFi UE based on its RSS values, where the first ANN is a multiple layer perceptron (MLP) and the second ANN is a convolution neural network (CNN). Moreover, the authors in [23] considered a spatial modulation aided indoor visible light communication system with a random receiver orientation, where two ANNs are proposed to predict the channel state information (CSI) with high accuracy and resolution.

The joint position and orientation estimation techniques proposed in the LiFi literature (such as in [20], [21], [22] 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 [24]. 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 [24]. 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 [25]. 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 [25]. However, for the case of mobile LiFi UEs, such processing delay may exceed the maximum amount of time allocated to serve all the mobile UEs, and therefore, can not be tolerated. In fact, since UEs are mobile, they might change their instantaneous positions/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 a performance degradation. This problem is known as channel aging, i.e., the LiFi channel coefficients are outdated after the processing time. The channel aging problem is a very known problem in the literature of wireless and mobile RF communications. However, to the best of our knowledge, this problem has been never studied or addressed in the LiFi literature.

C. Contributions and Outcomes

Against the above background, a proactive optimization (PO) approach is proposed in this paper 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 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 associated posterior 3D position and orientation relative 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 [19], [24], [26]. Then, the received SNR values at the APs associated to the first $N$ time steps of each sequence are calculated and recorded into a dataset as features. On the other hand, the 3D position and orientation relative to time steps $[N+1, N+L]$ 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 predict the posterior 3D position and orientation of the UE.

The performance of the designed LSTM model is evaluated in terms of prediction error, precision, and computational time, and it 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 [20]. In addition, as an application of the proposed PO approach, a typical optimization problem is considered. This optimization problem aims at maximizing the sum-rate of a multiuser multiple-input single-output (MISO) 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 non-linear and non-convex. One way to solve the invoked problem is by using the convex-concave procedure (CCP), which is an organized heuristic for solving non-convex problems. However, the issue with this approach is the number of iterations required to converge to an optimal solution, which induce a high processing delay at the LiFi physical layer, and therefore, can cause the channel aging problem. To deal with this issue, the proposed PO approach is applied and the formulated problem is solved proactively using CCP. Simulation results show a 0.9% sum-rate performance gap between the performance of the exact LiFi channel coefficients and the one of the predicted channel coefficients, while providing a real time precoding solution. This demonstrates the potential of the proposed PO approach is able to provide a near-optimal and real-time service for the mobile LiFi 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 MISO LiFi systems with QoS constraint. Sections VI and VII present the simulation results and the conclusion, respectively.

The list of main symbols used in the paper are summarized in Table I. In addition, upper case bold characters denote matrices, whereas lower case bold characters denote vectors. The operators $(\cdot)^T$ and $(\cdot)^{\perp}$ denote the transpose and the pseudo-inverse operators, respectively. 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. For every two real numbers $a$ and $b$ such that $a < b$, the function $U_{[a,b]}(\cdot)$ denotes the unit step function within $[a,b]$, 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 Model and Problem Statement

We consider the indoor LiFi system presented in Fig. 1, which consists of $M$ APs installed at the ceiling of the indoor
environment. 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 called 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 uplink data transmission and downlink data reception, respectively. The communication between the APs and each UE is bidirectional. Specifically, in the downlink, the APs employ the VL spectrum for transmitting the information that is received by each UE 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. Hence, there is no interference in this system 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 (IM/DD) is considered. For all $k \in [1, K]$, the downlink received signal at the $k$th UE at each time slot $t > 0$ is expressed as [26]

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

(1)

where $h_k(t)$ represents the instantaneous downlink $M \times 1$ channel gain vector between the APs and the $k$th UE, and its expression is given in [7] and [20]. Moreover, in (1), $s(t)$ represents the $M \times 1$ information-bearing signal broadcast by the APs at time slot $t$, which contains a mixture of the data intended to the $K$ UEs, and $n_k(t)$ is the instantaneous additive white Gaussian noise (AWGN) experienced at the PD of the $k$th UE that is $\mathcal{N}(0, N_0 B_{VL})$ distributed, such that $N_0$ is the noise power spectral density and $B_{VL}$ is the VL bandwidth of the system.

The performance of the considered LiFi system depends heavily on the instantaneous $K \times M$ channel matrix $H(t) = [h_1(t), h_2(t), \ldots, h_K(t)]^T$, which in turn depends on the positions of the APs as well as the instantaneous 3D position and orientation of each UE [20]. 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 $R_k(t) = R_{\alpha_k(t)}R_{\beta_k(t)}R_{\gamma_k(t)}$, where $R_{\alpha_k(t)}$, $R_{\beta_k(t)}$ and $R_{\gamma_k(t)}$ are expressed as shown in (2), at the bottom of the 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 $n_k^{new}(t) = R_k(t)n_k$, where $n_k$ 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 $H(t)$. In this context, assuming that the channel matrix $H(t)$ 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, resource allocation, precoding/beamforming, and AP selection, etc, are generally complex to solve and time-consuming, such as in [28], [29], [30], [31], [32], and [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 the high computational load [25]. 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 UEs [25].

Let us consider an optimization problem $P[H(t)]$ that aims at enhancing the performance of the mobile 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 $P[H(t)]$ at each time slot $t$, which increases as the number of mobile UEs and/or APs increases. Within the time interval $\Delta t$, the channel matrix $H$ evolves from $H(t)$ to $H(t + \Delta t)$, since the UEs 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 $P[H(t)]$ at time slot $t$ may no longer be optimal after the processing time $\Delta t$. In other words, the obtained solution, which is optimal for $H(t)$, is not optimal for $H(t + \Delta t)$ and can imply a performance loss to the system. This problem is known as channel aging, i.e., the channel matrix $H(t)$ is outdated at time slot $t + \Delta t$, and this is actually a very known problem in the wireless and mobile communication literature [34], [35]. Based on the above discussion, a PO approach is proposed in this paper 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. First, the basics of the proposed approach will be discussed. Then, its detailed implementation is investigated.

A. Proposed Approach

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

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

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

### B. RSS Collection Phase

In this phase, $N \in \mathbb{N}\{0\}$ 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 $p_k(j)$. First, in order to cancel any inter-user interference in this phase, the total available IR bandwidth, denoted by $B_{IR}$, 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 direct current (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 DC biasing current 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 $z_{k,i} = g_{k,i}(j)s_k + \omega_i$, where $g_{k,i}(j)$ is the total uplink channel gain between the $k$th UE and the $i$th AP at time slot $j$, and its expression is given in [7] and [20], and $\omega_i$ is an AWGN experienced at the $i$th AP that is $N(0, \sigma_n^2)$ distributed, such that $\sigma_n^2 = \frac{K_{IR}B_{IR}}{R}$, in which $B_{IR}$ is the IR bandwidth of the system.

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

$$r_{k,i}(j) = \frac{\lambda^2_0 g_{k,i}(j) I_{DC}^2}{\sigma_n^2}.$$  

(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

$$r_k(j) = [r_{k,1}(j), r_{k,2}(j), \ldots, r_{k,M}(j)],$$

(4)

which depends mainly on the instantaneous 3D position and orientation vector of the $k$th UE $p_k(j)$ at time slot $j$. Consequently, as shown in Fig. 3, within 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 $k$th UE that is expressed as

$$r_{k,\text{total}}(t) = [r_k(t - N + 1), r_k(t - N + 2), \ldots, r_k(t)].$$  

(5)

### C. Prediction Phase

In this phase, the goal is to predict, at each time slot $t$, the posterior 3D position and orientation for each 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 $p_k(t + L)$ of the $k$th UE, based on its associated vector of RSS values $r_{k,\text{total}}(t)$ collected between time slots $t - N + 1$ and $t$. As was mentioned in the RSS collection phase in Section III-B, for all $k \in [1, K]$, the vector of RSS values $r_{k,\text{total}}(t)$ collected between time slots $t - N + 1$ and $t$ is

$$R_{\alpha_k(t)} = \begin{bmatrix} \cos \alpha_k(t) & -\sin \alpha_k(t) & 0 \\ \sin \alpha_k(t) & \cos \alpha_k(t) & 0 \\ 0 & 0 & 1 \end{bmatrix}, \quad R_{\beta_k(t)} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos \beta_k(t) & -\sin \beta_k(t) \\ 0 & \sin \beta_k(t) & \cos \beta_k(t) \end{bmatrix}, \quad R_{\gamma_k(t)} = \begin{bmatrix} \cos \gamma_k(t) & 0 & \sin \gamma_k(t) \\ 0 & 1 & 0 \\ -\sin \gamma_k(t) & 0 & \cos \gamma_k(t) \end{bmatrix}.$$  

(2)
such that i.e., there exists a deterministic vector-valued function \( F \) a function of the instantaneous 3D position and orientation of the time slots \( t - N + 1, t \), i.e., there exists a deterministic vector-valued function \( F \) such that

\[
\mathbf{p}_k(j) = F(\mathbf{r}_k(j)).
\]

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 \( k \)th UE within the time interval \([t - N + 1, t]\).

For all \( k \in [1, K] \), since the \( k \)th 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

\[
\begin{bmatrix}
\mathbf{p}_k(t + L) \\
\mathbf{p}_k(t + L - 1) \\
\vdots \\
\mathbf{p}_k(t)
\end{bmatrix} = \mathbf{G}
\begin{bmatrix}
\mathbf{p}_k(t) \\
\mathbf{p}_k(t - 1) \\
\vdots \\
\mathbf{p}_k(t - N + 1)
\end{bmatrix}.
\]

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 \( t \),

\[
\begin{bmatrix}
\mathbf{r}_k(t + L) \\
\mathbf{r}_k(t + L - 1) \\
\vdots \\
\mathbf{r}_k(t)
\end{bmatrix} = \mathbf{J}
\begin{bmatrix}
\mathbf{r}_k(t) \\
\mathbf{r}_k(t - 1) \\
\vdots \\
\mathbf{r}_k(t - N + 1)
\end{bmatrix}.
\]

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 \( k \)th UE and the \( M \) APs. Although the contributions of the NLOS components will improve the prediction accuracy, similar to what was shown in the estimation problem invoked [20], their inclusion in the prediction process is not straightforward from an optimization point of view, similar to the case of maximizing an observed predictive likelihood function. This is basically due to their complex expressions [7], [20].

To overcome this issue, an approximate parametric vector-valued function \( \mathbf{J}(\mathcal{W}, \cdot) \) 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 \( k \)th UE relative to time slot \( t + L \) can be obtained as

\[
\begin{bmatrix}
\mathbf{p}_k(t + L) \\
\mathbf{p}_k(t + L - 1) \\
\vdots \\
\mathbf{p}_k(t)
\end{bmatrix} = \mathbf{J}(\mathcal{W},
\begin{bmatrix}
\mathbf{r}_k(t) \\
\mathbf{r}_k(t - 1) \\
\vdots \\
\mathbf{r}_k(t - N + 1)
\end{bmatrix}).
\]

The details on how the approximate parametric vector-valued function \( \mathbf{J} \) and the optimal set of parameters \( \mathcal{W}^* \) 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 \( \mathbf{p}_k(t + L) \) of the \( k \)th UE associated to time slot \( t + L \) is obtained and its associated predicted \( M \times 1 \) channel gain vector \( \mathbf{h}_k(t + L) \) can be calculated at time slot \( t \). Consequently, the predicted \( K \times M \) channel matrix \( \mathbf{H}(t + L) = [\mathbf{h}_1(t + L), \mathbf{h}_2(t + L), \ldots, \mathbf{h}_K(t + L)]^T \) can be obtained at time slot \( t \).

D. Optimization Phase

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

The accuracy of predicting the channel matrix $\mathbf{H}(t + L)$ at time slot $t$ depends mainly on the speeds of the LiFi users, which might be different depending on several factors, including the age, the activity, and the physical form and conditions of the LiFi user, etc. More importantly, the higher the speed is, the more difficult it is to predict the channel gains. In fact, when the speed increases, the travelled distance increases, and the evolution of the posterior channel gain will naturally increase, which rises the uncertainty in the posterior channel gain. With this being said, the error between the actual channel matrix $\mathbf{H}(t + L)$ and the predicted channel matrix $\mathbf{H}(t + L)$ will be high. This error will make the solution of problem $\mathcal{P}[\hat{\mathbf{H}}(t + L)]$, along with any link adaptation function, such as interference cancellation, precoding, beamforming, or power control, not optimal. To overcome this problem, the prediction method, either an AI/ML method, a non-AI/ML method, or a hybrid method, should have the capacity to provide high accurate prediction for all possible speeds of typical indoor users, which can vary between 0 to 3 meters per seconds at maximum.

IV. Joint Prediction of Indoor LiFi User Position and Orientation

A. Methodology

In this section, and as discussed in Section III-C, our objective is to determine an approximate parametric vector-valued function $\mathbf{J}$ along with its optimal set of parameters $\mathcal{W}^*$ 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. 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 techniques, especially when a large amount of data is available [36]. 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 [36]. 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, and the high speed and the accurate processing requirements, which present big challenges to 6G wireless networks [37]. Motivated by this, DL has been applied to wireless communications, such as physical layer communications [37], [38], resource allocation [39], [40], and intelligent traffic control [41]. 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 are generated. All sequences have the same length $N + L_{max}$, where $L_{max}$ denotes the maximum posterior time slot index. Specifically, for all $q \in \{1, Q\}$, a random trajectory of length $N + L_{max}$ 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 $[p_{N+1}^{q}, p_{N+2}^{q}, \ldots, p_{N+L_{max}}^{q}]$ of $N + L_{max}$ 3D position and orientation vectors is randomly generated using the experimental-based indoor ORWP [26], where for all $n \in \{1, N + L_{max}\}$, $p_{n}^{q}$ is the 3D position and orientation vector of the $n$th time step of the $q$th sequence. The details of the experimental-based ORWP model employed here are presented in [26]. Then, the obtained sequence is recorded.

2) For all $n \in \{1, N\}$, the $1 \times M$ SNR vector $r_{n}^{q}$ is calculated based on the 3D position and orientation vector $p_{n}^{q}(n)$.

3) The features vector of the $q$th data point is the $1 \times N$ sequence of SNR vectors $[r_{1}^{q}, r_{2}^{q}, \ldots, r_{N}^{q}]$.

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

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 $\mathbf{J}$ that can map between the prior 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 $\mathbf{J}$ 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 [42], [43]. 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 [42], [43]. 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 [44]. 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 $\hat{J}$ is an LSTM network that is trained in the offline phase using the generated dataset. Hence, its optimal set of parameters $W^*$ that provides 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 $\hat{J}(W^*, \cdot)$ 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 $[r_k(t - N + 1), r_k(t - N + 2), \ldots, r_k(t)]$ 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 $\hat{J}(W^*, \cdot)$ in order to output the sequence of predicted posterior 3D position and orientation vectors of the $k$th UE $[\hat{p}_k(t), \hat{p}_k(t + 1), \ldots, \hat{p}_k(t + L)]$, where $L \in [1, L_{max}]$ 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., $\hat{H}(t + L)$. Finally, assuming a certain transmission strategy and a predefined performance metric, the associated optimization problem $P \left[ \hat{H}(t + L) \right]$ 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 LiFi UEs at time slot $t + L$ directly, without any processing delay at time slot $t + L$.

V. APPLICATION: PROACTIVE SUM-RATE MAXIMISATION OF MULTI-USER MISO 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 MISO 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 $u(t) = [u_1(t), u_2(t), \ldots, u_K(t)]^T$ to the $K$ UEs, 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 $V(t) = [v_1(t), v_2(t), \ldots, v_K(t)]$ presents the $M \times K$ 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 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 transfer characteristic of LEDs leads to a unique optical power...
C. Problem Formulation and Solution Approach

The design criterion of the considered LiFi system is to maximize the achievable sum data-rate of the LiFi system. Therefore, the weighted sum-rate metric is the performance metric to optimize. Hence, the question that arises naturally here is how to set the weights of users. Basically, the weighted sum rate is useful for prioritizing different LiFi users among others. However, in this application, there is no prioritization of any LiFi users over others since all LiFi users are assumed to belong to the same 6G service category, i.e., either eMBB, URLLC, or mMTC. As another application that can be considered in the future, we might adopt the weighted sum-rate as a performance metric and propose efficient techniques in setting the weights of LiFi users. Now, within the context of this paper, and 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 \( \mathbf{V}(t) \) can be obtained through the following optimization problem:

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

(17a)

s.t. \[ h_k^T(t) v_i(t) = 0, \forall (k, i) \in \{1, K\}^2 \& i \neq k, \]  

(17b)

\[ R_{th} \leq R_k \left( h_k(t), v_k(t) \right), \forall k \in [1, K], \]  

(17c)

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

(17d)

Problem \( \mathcal{P}\left[ \mathbf{H}(t) \right] \) 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 \( \mathcal{P}\left[ \mathbf{H}(t) \right] \). However, these approaches require a processing time that may exceed the maximum amount of time allocated to serve the different UEs, which raises the channel aging problem invoked in this paper. To overcome this issue, the proposed PO approach can be applied. Consequently, considering a posteriori time slot index \( L \), we are interested in solving at each time slot \( t \) the optimization problem \( \mathcal{P}\left[ \mathbf{H}(t+L) \right] \) that is expressed as follows.

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

(18a)

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

(18b)

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

(18c)

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

(18d)

Solving problem \( \mathcal{P}\left[ \mathbf{H}(t+L) \right] \) 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 \( \mathcal{P}\left[ \mathbf{H}(t+L) \right] \) 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

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

(19)

where \( \mathbf{X} = \text{diag}\left( \mathbf{x} \right) \) 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 \( \mathcal{P}\left[ \mathbf{H}(t+L) \right] \) can be re-expressed as

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

(20a)

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

(20b)

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

(20c)

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

\[ \frac{\partial^2}{\partial x^2} f(x) = \frac{\rho (\rho x^2 - 1)}{(\rho x^2 + 1)^2}, \]  

(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 \( \mathcal{P}'\left[ \mathbf{H}(t+L) \right] \) is not convex. To deal with this issue, we convexify problem \( \mathcal{P}'\left[ \mathbf{H}(t+L) \right] \) by employing the CCP proposed in [46]. By using CCP, and based on the description in [46], 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 \( \mathcal{P}'\left[ \mathbf{H}(t+L) \right] \), which is denoted by \( \mathcal{P}''\left[ \mathbf{H}(t+L), \mathbf{y}_j \right] \), is given by (22), as shown at the bottom of the next page.

Problem \( \mathcal{P}''\left[ \mathbf{H}(t+L), \mathbf{y}_j \right] \) is a convex optimization problem that depends on the linearization point \( \mathbf{y}_j \) and can be solved efficiently using standard optimization packages [47], [48]. The detailed iterative algorithm for solving problem \( \mathcal{P}\left[ \mathbf{H}(t+L) \right] \) is given in Algorithm 1, where the initial point \( \mathbf{y}_0 \) is a random feasible point that satisfies the constraints of problem \( \mathcal{P}\left[ \mathbf{H}(t+L) \right], \mathcal{g}(\cdot, \cdot) \) is the objective function in (22a) of problem \( \mathcal{P}''\left[ \mathbf{H}(t+L), \mathbf{y}_j \right], \epsilon \) is a gap threshold, and \( T_{\text{max}} \) is a maximum number of iterations. Finally, once the precoding matrix \( \mathbf{V}^*(t) \) is obtained, it is applied directly at time slot \( t + L \). Consequently, for all \( k \in [1, K] \), the instantaneous achievable rate at the \( k \)-th UE at each time slot \( t \) can be expressed as \( R_k \left( \mathbf{h}_k(t), \mathbf{v}_k(t+L)^* \right) \).

D. Complexity Analysis

In this part, we evaluate the computational complexity of the ZF precoding scheme. In Algorithm 1, we employ the well known interior point algorithm (IPA) in solving the invoked
Algorithm 1 Iterative Algorithm for Solving $\mathcal{P}'' \left[ \tilde{\mathbf{H}}(t + L) \right]$

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

The worst-case complexity of our proposed schemes and of the IPA at most $J_{\text{max}}$ times, and thus, we are employing the IPA at most $J_{\text{max}}$ times. Based on (22), the number of required recursive steps to reach a local solution is $O(J_{\text{max}}K)$.

VI. SIMULATION RESULTS

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

A. Simulations Parameters and ANNs Specifications

In this paper, we consider a typical indoor environment with dimensions $10 \times 10 \times 3$ m$^3$. The indoor environment is equipped with $M = 16$ APs that are arranged on the vertices of a square lattice over the ceiling of the room. In addition, a LiFi UE is a typical smartphone with dimensions $3.8 \times 7 \times 1$ cm$^3$. The IR-LED and the PD of each LiFi UE are adjacent to each other and are placed at screen of the smartphone, exactly at 6 cm above the center. The values of the main channel parameters used in the simulations are adopted from [20]. In addition, the parameters used throughout the paper are shown in Table II. The architecture of the LSTM model is shown in Table III. Moreover, the CNN model proposed in [20] is considered for comparison purposes and its design is optimized for the adopted simulation environment. The designs of the LSTM and CNN models are performed using the programming environment Python 3 and the Keras library developed by Google’s TensorFlow team in 2017 [50]. 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. Learning and Prediction Performance Evaluation

Fig. 6 presents the training and validation losses of the designed LSTM and CNN models, measured in terms of the mean-squared-error (MSE), versus the training epoch index. As it can be seen from this figure, the training and validation losses decrease as the epoch index increases, which

\[
\mathcal{P}'' \left[ \tilde{\mathbf{H}}(t + L), \mathbf{y}_j \right] : \quad \min_{\mathbf{x}} \sum_{k=1}^{K} \frac{1}{2} \log \left( 1 + \rho y_{j,k}^2 \right) - \rho y_{j,k} \times (x_k(t) - y_{j,k}) ,
\]

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

\[
\|H^\dagger(t) \text{diag} (x(t))\|_\infty \leq 1.
\]
Table IV. However, for the pitch angle $\beta$ resulting from the LSTM and CNN models are presented in apply for the yaw angle the same interpretations established for the positioning error of the orientation angles yaw $\alpha$ and roll $\gamma$ that the instantaneous position error increases as the posterior time slot index increases. This result is expected since, as 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. 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 $0.1 \times Q = 10^3$, 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 $\frac{3}{Q} = 0.03$ milliseconds and $\frac{6.56}{Q} = 0.07$ milliseconds 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.

C. Sum Rate Performance Evaluation

In this subsection, we consider the proactive sum-rate maximisation of the multiuser MISO 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 $\mathbf{H}(t + L)$ 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. This baseline presents the upper bound of the system performance.

2) Proposed PO: The predicted instantaneous channel matrix $\hat{\mathbf{H}}(t + L)$ 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 $\hat{\mathbf{H}}(t + L)$ 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 $\mathbf{H}(t)$ 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 $t + L$. This baseline presents the performance of the system with channel aging.
Table IV

|                      | $L = 1$       | $L = 2$       | $L = 3$       | $L = 4$       |
|----------------------|--------------|--------------|--------------|--------------|
| **Position**         | LSTM         | CNN          | LSTM         | CNN          |
|                      | 0.1789 m     | 0.4742 m     | 0.2136 m     | 0.5192 m     |
| **Yaw angle $\alpha$** | 22.4266°     | 32.6992°     | 22.8108°     | 32.4743°     |
| **Pitch angle $\beta$** | 2.5974°      | 2.6003°      | 2.6013°      | 2.6068°      |
| **Roll angle $\gamma$** | 4.3254°      | 4.3262°      | 4.3212°      | 4.3358°      |

Fig. 8. CDF of the prediction error of the orientation angles yaw $\alpha$, pitch $\beta$ and roll $\gamma$.

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.
- The CCP approach (Algorithm 1).

In line with the above, Fig. 9 presents the average sum rate of the considered 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 target rate threshold (QoS) per UE is $R_{th} = 1$ 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 Upper Bound, Fig. 9 highlights the performance degradation that is caused by the channel aging problem, where the peak gap between the average sum rates associated to Upper Bound 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 peak gap between the average sum rates associated to Upper Bound and the proposed PO is less than 7%. On the other hand, Fig. 9 shows that the LSTM model outperforms the CNN model.

1The adopted solver is fmincon, which is a predefined MATLAB solver [51]. In addition, 100 distinct initial points were randomly generated within the feasibility region of the optimization variables in order to converge to the optimal solution. Specifically, through the use of the fmincon solver, each initial point will lead to a given local extremum. Then, once all local extrema are collected, a simple brute force search over the obtained extrema is applied to obtain the optimal solution. Although this heuristic approach suffers from its high complexity, it was demonstrated that it is very effective in finding the optimal solutions of non-convex problems as shown in [52], [53], [54], and [55]. Nevertheless, it is important to mention that the optimal solutions of the considered problems can also be obtained using the technique proposed in [56], which has a complexity of $O\left(\frac{1}{\epsilon^2}\right)$ when the target accuracy of the solution is less than $\epsilon$.Authorized licensed use limited to the terms of the applicable license agreement with IEEE. Restrictions apply.
the one of the optimal optimization approach (at least that the CCP approach has a lower computational time than versus the number of LiFi UEs. This figure demonstrates obtaining the best ZF precoder for the considered LiFi system optimal optimization approach and the CCP approach for their target QoS.

Due to the fact that their channel realizations can not satisfy users that are admitted to the networks decreases, and this is since when the rate threshold $R_{th}$ decreases as the rate threshold $R_{th}$ increases, the number of users that are admitted to the networks decreases, and this is due to the fact that their channel realizations can not satisfy their target QoS.

Fig. 11 presents the average computational time of the optimal optimization approach and the CCP approach for obtaining the best ZF precoder for the considered LiFi system versus the number of LiFi UEs. 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 lower computational time for the considered problem. Moreover, assuming that 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 $L = 1$, i.e., at each time slot $t$, 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 ZF precoder can be applied directly at time slot $t + 1$ without any processing delay.

D. Practical Deployment of the PO Approach

When applying AI/ML techniques to enhance and/or replace a certain function in the LiFi air interface, the associated key performance indicators (KPIs), such as performance gain compared to legacy/conventional non-AI/ML techniques (throughput, bit error rate, etc.), inference latency, complexity, size and memory storage of AI/ML models, overhead, etc., should be studied. However, other critical aspects regarding generalization and scalability issues should be carefully analyzed. Precisely, for the proactive management problem that we are investigating in this paper, the objective is to design the lowest number of AI/ML models that can generalize well over all possible scenarios (speeds, number of users, duplex mode, etc.) and configurations (number of APs, carrier frequencies, size/shape of the room, etc.), while providing acceptable tradeoffs between KPIs compared to legacy/conventional non-AI/ML techniques. On the other hand, other critical aspects regarding the applicability and deployment in real world scenarios, ML model operationalization management (MLOps), and life cycle management, etc. should be carefully investigated. This includes AI/ML models switching depending on the agreed scenarios and configurations, the activation/deactivation of AI/ML models, performance monitoring to maintain the target QoS to the LiFi users, fallback mechanisms to legacy non-AI/ML techniques when the AI/ML fails or its performance drops, retraining and/or finetuning the AI/ML models when the propagation conditions change, etc.

VII. Conclusion

In the context of mobile LiFi systems, uplink outdated CSI feedback that is resulting from the mobility of LiFi users with different velocities impact the system performance remarkably. This problem is a known as the channel aging problem. With the goal of overcoming the LiFi channel aging problem, a PO approach for is proposed in this paper. The core of the proposed technique is an LSTM network that is capable of predicting posterior positions and orientations of mobile users based on some prior information on the RSS values at the APs, which are then 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 near-optimal and real-time service for mobile LiFi users. Through various simulations, the performance of the proposed PO approach is investigated and the obtained results demonstrated the potential of the proposed PO approach in alleviating the LiFi channel aging problem.

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This article presents a chapter of the Ph.D. thesis of Dr. Mohamed Amine Arfaoui [1] within the Gina Cody School of Engineering and Computer Science, Concordia University, Montreal, QC, Canada, and it was submitted prior to joining Interdigital Canada Ltee., Montreal.

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