Lighting Up Dynamic Networks : AP Assignment Strategy for QoS and Energy Efficiency in HLWNets

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***Abstract*—Light Fidelity (LiFi) is a recent wireless technology that offers high data rates, low power consumption and do not interfere with radio frequency technologies. As a result, LiFi access points emerge as promising complements to Wi-Fi access points for hybrid LiFi/Wi-Fi networks (HLWNets). This combination can offer high data rates and energy efficiency. However, to fully benefit from hybrid networks, it is crucial to efficiently assign stations, whether with LiFi or Wi-Fi access points. In this paper, we formulate the AP assignment problem as an optimization problem. As a solution, we present an AP assignment strategy, in which we elaborate an algorithm with a low computational complexity. The algorithm allows to dynamically assign STAs to APs and benefits from the combination of the two technologies to enhance network performance (energy consumption and throughput satisfaction).**

***Index Terms*—LiFi, Wi-Fi, Hybrid Networks, Energy Efficiency, User satisfaction, Operational Network.**

I. Introduction

LiFi technology uses visible light, ultraviolet, and infrared spectrums for data transmission, which reduces power consumption. With its wide free-license spectrum, it is a promising solution to meet growing network demands. However, LiFi's limited range and line-of-sight requirement make it insufficient for uninterrupted network connectivity, making Wi-Fi the perfect complement for indoor communications.

In this paper, we study the assignment problem for dynamic hybrid LiFi/Wi-Fi networks (HLWNETs). Combining these two technologies adds a new layer of complexity to assign stations (STAs) to access points (APs). To address this problem, researchers formulate it as an optimization problem in [1], [2] and [3]. Their models assume static networks, which are not always representative of real-world scenarios. In reality, in many cases, the network is dynamic and can evolve over time due to factors such as STA mobility, changes in throughput demand of STAs, or arrivals and departures of STAs. A couple of works address dynamic networks in which STAs are mobile [4], [5]. In [4], the authors formulate the assignment and resource allocation problem as an optimization problem and use a fuzzy logic approach to solve it. In [5], the authors propose a *Multi-Armed Bandit Model* to tackle the dynamic AP assignment problem in LiFi networks. The model consists in updating the probability of selecting an AP by taking into account both the previously learned information and the environmental criteria (such as the STAs distribution).

Another issue with dynamic HLWNETs is the *Handovers Management*. The handover mechanism consists in assigning a STA from one AP to another. It can cause a temporary degradation in the throughput or interrupt the network connection for the STA. These handovers can be very frequent due to the small range of LiFi and the wide overlapping areas between APs. In [6], the handover problem is formulated as a joint optimization problem that considers resource allocation and handover management. The authors consider the throughput loss caused by handovers to trigger the mechanism. In [7], authors propose a dynamic resource allocation and assignment scheme, where their LiFi model considers the handover overhead time. The authors assume a stability period during which the network remains stable (e.g., constant throughput demand and no mobility). This assumption enables them to execute the resource allocation and assignment scheme at regular intervals without the risk of stale information.

The mentioned papers mostly focus on throughput as a metric for network performance. However, these papers neglect the energy consumption and the MAC layer (which may introduce a bias and negate STAs satisfaction). In this paper, our contributions are as follows: (i) We propose a repeated local search algorithm and an objective function that considers energy consumption and throughput satisfaction by incorporating TDMA for LiFi and CSMA/CA for Wi-Fi. (ii) We also propose a dynamic assignment strategy to lower both the assignment computational complexity, and the rate of handovers.

The rest of this paper is as follows: Section 2 presents our solution for dynamic assignment, followed by the numerical results in Section 3. Finally, Section 4 concludes the paper.

II. Dynamic AP assignment in a LiFi/Wi-Fi network

First, we propose an objective function to score the quality of the STAs assignments. The network dynamicity is caused by events such as the arrival or departure of a STA within the coverage area of an AP.

A. *Optimization problem*

We represent the assignments between STAs and APs by a matrix $\mathbf{Y} = [y_{ap,sta}]_{1 \le ap \le m; 1 \le sta \le n}$ of dimension $m * n$, where m is the number of APs, and n the number of STAs. $y_{ap,sta}$ equals 1 if sta is assigned to ap, and 0 otherwise. We consider the same problem formulation as [3], where we formulate the AP assignment issue as an optimization problem subject to a set of constraints. Unlike [3], we apply our objective function to dynamic networks and adapt LiFi model to align with the specifications of the manufacturer [8].

The objective function aims to maximize the throughput of STA and minimize the overall energy consumption (for both, APs and STAs). we express it as :

$$\text{maximize} \quad F(\Phi, \Psi) \tag{1}$$

where Ψ is the total network energy consumption (energy consumed by every STA and every AP). Φ is the throughput metric that accounts for the fairness between the different STAs. We formulate Φ as :

$$\Phi = \left(\prod_{\substack{ap \in APs,\ sta \in STAs\ : \\ y_{ap,sta}=1}} S_{ap,sta} \right)^{1/n} \tag{2}$$

where $S_{ap,sta}$ denotes the throughput satisfaction if sta is assigned to ap. To align with the Wi-Fi standard, we adopt the CSMA/CA for the Wi-Fi MAC layer [9], and TDMA mechanism for the LiFi MAC layer [8]. We define our objective function F in Equation 3. We use Φ_{max} (resp. Φ_{min}) to denote the maximum (resp. minimum) STAs satisfaction, which is 0 (resp. 1). Analogously, we denote by Ψ_{max} (resp. Ψ_{min}) the maximum energy consumption (resp. minimum).

$$F(\Phi, \Psi) = \left(\frac{\Phi - \Phi_{min}}{\Phi_{max} - \Phi_{min}} \right) \times \alpha + \left(\frac{\Psi_{max} - \Psi}{\Psi_{max} - \Psi_{min}} \right) \times (1 - \alpha) \tag{3}$$

We use α (resp. $1-\alpha$) to denote the weights assigned to the throughput metric Φ (resp. the consumption metric Ψ). Note that F increases with increasing values of the throughput Φ or with diminishing values of the energy consumption Ψ.

B. *Repeated Local Search - RLS*

To solve the optimization problem, we employ a local search-based heuristic to find a feasible solution. We then adapt this heuristic to account for the network dynamicity. Starting from a predetermined assignment matrix $\mathbf{Y}$, the heuristic advances toward its final solution by exploring the neighborhood of the current matrix. We define this neighborhood as the set of matrices that can be obtained by making a single change to the assignment between a STA and an AP. At each iteration, the heuristic browses every STA. For each of them, it computes $F(\Phi, \Psi)$ to determine the best AP for each STA. The current iteration ends with the update of the assignment matrix so that the best-explored neighborhood assignment becomes the new current assignment in the updated $\mathbf{Y}$. The process repeats I times until convergence is found (no changes improve the score). To mitigate the odds of getting stuck in a local optimum, we repeat R times the local search with different random initial assignments. Then, we keep the assignment matrix with the highest score. This approach is known as the repeated local search (RLS).

As mentioned previously, we need to adapt the application of the RLS algorithm to avoid two problems: (i) It may exhibit low reactivity due to its computational complexity $\mathcal{O}(n^2 \cdot m \cdot I \cdot R)$, which can prevent real-time assignment updates, especially when two events occur within a short timeframe; (ii) Its application may lead to numerous changes in the STAs assignment (handovers), resulting in significant overhead traffic and connectivity disruptions. To prevent these problems, the assignment policy should favor assignments that reduce the rate of changes. We measure this rate through a metric that we name *change rate*. To compute *change rate*, we divide the number of STAs that experience a change of assignment by the total number of assignments.

C. *Dynamic assignment management*

a) Best effort: a simple way to cope with computational complexity and *change rate* problems, is to only assign the new STA, hence, without changing the others. Whenever a new STA appears on the network, we assign this STA to the AP that offers the best score with the objective function. Note that nothing is done upon a STA departure. If an AP is unused due to the departures of all its stations, it is turned off (unless this would compromise the entire coverage that has to be guaranteed). We denote this approach by *Best effort algorithm*. This algorithm has a low complexity $\mathcal{O}(m)$, and reduces drastically the *change rate* as only the new STAs change their assignments.

b) Hybrid approach: the Best effort algorithm may deviate from the best matrix assignment in the long run. We address this by introducing a *Consolidation Step* which depends on a threshold $\mathcal{T}$ taking its values between 0% and 100%. We define $\mathcal{R}$ as the deviation rate of the current score from the obtained score at the last consolidation step ($\mathcal{R} = \frac{\text{previous score} - \text{current score}}{\text{previous score}}$). Every time $\mathcal{R} \ge \mathcal{T}$, the consolidation step takes place, and we run the RLS algorithm to update the current assignment. Otherwise, we apply the Best effort algorithm.

In the numerical evaluation, we consider different threshold values $\mathcal{T}$ for the consolidation step. This *occurrence rate* is defined as the number of consolidation steps that occur during the simulation over the total number of events.

III. Numerical Results

A. *Use case*

Our use case is an indoor downlink scenario based on an office floor configuration as proposed in [10]. The environment is composed of multiple cubes, each representing 4 desks. Each desk is equipped with a LiFi AP and can support up to 4 STAs, as mentioned in [10]. The office floor also has a total of 9 Wi-Fi APs.

We consider a probabilistic model to simulate the events (arrival or departure of a STA) whose parameters vary with the time of the day (e.g., to reflect that arrivals are more likely at certain hours of the day). This model aims to capture the typical activity in an enterprise. Starting from a certain number of STA, we run this model at least 10 times. Figure 1 shows the average number of STAs throughout the day. Note that the dashed lines represent the minimum and maximum number of STAs. We observe numerous arrivals in the morning until 9AM and at the end of the lunch break (1:30PM). We also observe numerous departures at the beginning of the lunch break (12PM) and at the end of the day (6PM). The scenario reaches its maximum number of STAs and remains stable during the working hours (between 9AM-12PM and 2PM-6PM). The number of STAs also remains stable during lunchtime (between 12:30PM and 1:30PM). We compare 3

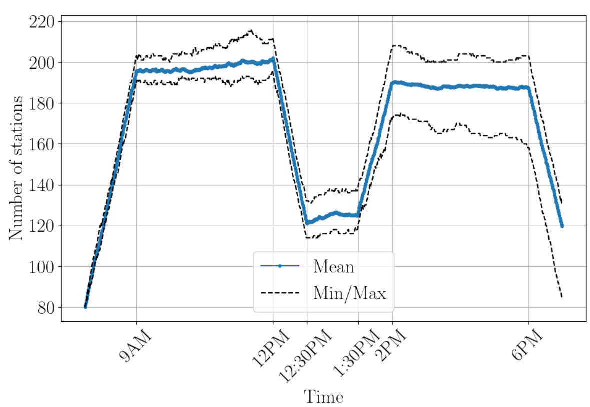


Fig. 1. Number of STAs over time.

different values with our approach: *a)* $\mathcal{T}$ equals 0%: we run the RLS algorithm whenever a new event occurs. *b)* $\mathcal{T}$ equals infinity: we simply apply the Best effort algorithm to assign new STAs. *c)* $\mathcal{T}$ equals either 2%, 5% or 10%: we apply the consolidation step whenever the potential gain exceeds 2%, 5% or 10% (Hybrid approach). Additionally, we compare those approaches with a classical one based on the Received Signal Strength Indicator (RSSI). This approach assigns every STA with the AP that provides the best RSSI (regardless of the current number of STAs already assigned to this AP). We use a Python simulator to implement the analytical models presented in [3], along with the described use case and our solutions. We consider the parameters proposed in [3] and [8] for our simulations. The additional parameters related to our approaches and the dynamicity of the network are presented in Table I. Note that, for each event, we repeat evaluation at least 10 times and average the obtained results. For the sake of clarity, we choose not to display the first and third quartiles in Figure 2, as they almost coincide with the average.

B. Discussion

Table II presents the average *change rate* between two consecutive consolidation steps alongside the occurrence rate,

Parameter	**Value**
Scenario	
Number of Cubes	24
Number of Wi-Fi APs	8
Number of LiFi APs	4 per Cube
Number of STAs	80–220
Events	
Number of events p	1400
Threshold $\mathcal{T}$	0%, 2%, 5%, 10%, ∞
Wi-Fi settings	
Standard	802.11ax
LiFi settings	
Transmission consumption	5 Watt

TABLE I
ADDITIONAL PARAMETERS USED IN THE SIMULATION. OTHER PARAMETERS, ARE FOUND IN [3], [8].

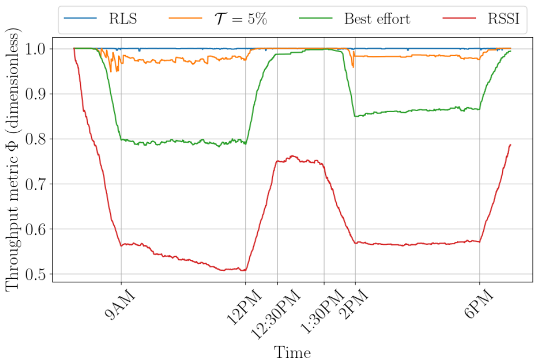
which denotes the rate at which consolidation steps occur upon new events (arrival, or, departure of a STA). We notice that even with a small value of $\mathcal{T}$ (i.e., 2%), the occurrence rate remains low between 0.3% and 1%, but the *change rate* (following a consolidation step) can be high (45% to 67%).

Approach	**Threshold $\mathcal{T}$**	**Occurrence rate**	***Change rate***
RLS	**0%**	100%	45%
Hybrid	**2%**	1%	58%
Hybrid	**5%**	0.7%	58.4%
Hybrid	**10%**	0.3%	67%
Best effort	∞	0%	0%
RSSI	/	/	0%

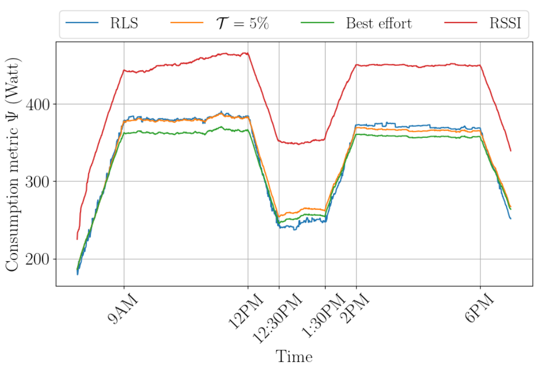
TABLE II
THE RATES OF CHANGE AND OCCURRENCE FOR DIFFERENT VALUES OF $\mathcal{T}$.

In Figure 2(a), we present the overall throughput satisfaction of the STAs. We observe that the RLS algorithm (i.e. $\mathcal{T} = 0$) is able to fully meet the STAs requirements. The approach with $\mathcal{T}$ set to 5% is able to meet most of the STAs demands, with an average satisfaction of approximately 97%. The Best effort (i.e. $\mathcal{T} = \infty$) and the RSSI approaches struggle to adapt to the different events and satisfy STAs demands. Nevertheless, the Best effort algorithm is able to reach 87% of the throughput satisfaction during working hours, unlike the RSSI approach which only reaches 55%.

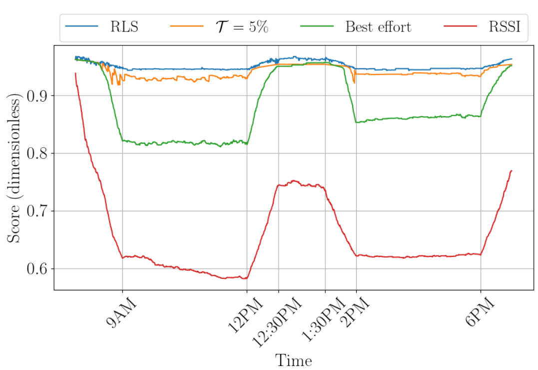
We show in Figure 2(b) the overall energy consumption of the network. We notice that the RLS algorithm adapts perfectly its energy consumption according to events (as highlighted with the arrows on the figure). Indeed, this approach consumes more during working hours (9AM-12PM and 2PM-6PM) and consumes less during lunch hours (12:30PM-1:30PM) compared to the other approaches. We also notice that when $\mathcal{T}$ is set to 5%, the approach adapts the energy consumption according to traffic demand (e.g., turning off AP when the occupancy rate equals zero). These energy consumption adaptations are obtained thanks to the updates made in the consolidation steps. The Best effort algorithm manages to adapt its energy consumption (as indicated by the arrows in this figure). However, it is made at the expense of the throughput satisfaction (as shown in Figure 2(a)). Indeed, this



(a) The overall throughput satisfaction of the STAs during a day.



(b) The total network energy consumption during a day.



(c) Score of the objective function during a day.

Fig. 2. Performance results using different approaches and their adaptation according to a daily STAs traffic in a company.

approach assigns new STAs with an AP without changing the assignment of other STAs. This may lead to the expensive operation (in terms of energy) of turning on an AP only for the sake of a single STA. Consequently, the Best effort algorithm does not favor turning on an AP (which was previously turned off) to save energy, even when the current number of STAs increases. Finally, we observe that the RSSI approach leads to a relatively high energy consumption. This approach consumes approximately 18% more than the others.

We plot the score for our approaches and RSSI in Figure 2(c). Approaches that trigger the RLS algorithm (RLS and $\mathcal{T} = 5\%$), offer the best score with a difference that never exceeds the threshold $\mathcal{T}$ by construction. The two other approaches (the Best effort and RSSI) deviate significantly from these scores, particularly the RSSI approach, which has a score 45% less during working hours. The RSSI approach does not take into account enough metrics to assign STAs, such as the number of STAs connected to an AP, and may assign multiple STAs with the same AP even if it is saturated.

IV. Conclusions

In summary, our paper proposes an approach to the AP assignment problem in dynamic LiFi/Wi-Fi networks. Our numerical results demonstrate that using the Best effort algorithm, complemented by the RLS algorithm when performance significantly decreases, can provide an effective solution for real-time STA assignment. This approach maintains a low level of computational complexity by sparingly utilizing the RLS algorithm, it achieves favorable scores adjustable through the threshold $\mathcal{T}$, and it reduces the number of handovers. With our objective function, network assignments successfully meet overall throughput requirements while also reducing the total energy consumption whenever feasible.

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