Seamless Handover in Hybrid VLC and WiFi network: a testbed scenario

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***Abstract*— In response to the growing demand for wireless communication in high-density environments, Visible Light Communication (VLC) has emerged as a promising complement to Radio Frequency (RF) communication. VLC technology utilizes light-emitting diodes (LEDs) to enable high-speed data transmission, while also providing illumination. In this paper, we propose a hybrid VLC/RF network with multiple VLC access points (APs) under a single WiFi AP. However, frequent handovers are typically required as users move within the network, leading to significant overhead and reducing throughput. To address this issue, we propose an intelligent handover solution based on fuzzy logic (FL) that leverages machine learning algorithms and considers received signal strength indicator (RSSI), channel state information (CSI), and user mobility to enhance handover decisions. We aim to develop a seamless and robust mechanism for horizontal handover (HHO) and vertical handover (VHO) in hybrid VLC/WiFi networks, which we implement in our testbed. Our experiments demonstrate that our proposed approach can achieve maximum handover times at 100ms and 400ms for HHO and VHO, respectively. We have fine-tuned different decision-making models, such as an AdaBoost C4.5 model, which can achieve up to 97.5% accuracy.**

Keywords—visible light communication, hybrid architecture, horizontal handover, vertical handover, OpenVLC.

I. Introduction

The surge in wireless data traffic has recently imposed a significant strain on existing communication networks. As a result, Visible Light Communication (VLC), which utilizes the visible light spectrum for data transmission, has emerged as an alternative communication channel. Meanwhile, WiFi remains the most widely used wireless communication technology for indoor environments. Integrated VLC and WiFi technologies have the potential to create more efficient, reliable, and secure communication systems, leading to benefits for various industries and applications. Hybrid VLC/RF systems are state-of-the-art solutions developed to address mobility/coverage and uplink transmission issues. Typically, the RF link serves as a backup link for VLC coverage gaps or as a VLC feedback and control channel. The advantages of hybrid networks utilizing WiFi and LiFi include high data rates due to the vast spectrum offered by VLC, non-interference with other systems due to the use of a distinct electromagnetic spectrum, and RF's all-encompassing coverage. However, due to users' erratic movements and the short-range nature of VLC equipment, the network would experience continuous handover. Therefore, a intelligent system management is necessary for the hybrid system to optimize all control and operation functions, including seamless handover between VLC and RF networks. The handover solution is what we are focusing on solving.

In this paper, we present a comprehensive study of handover mechanisms in hybrid networks, specifically focusing on the combination of VLC and WiFi networks. Firstly, we provide an up-to-date literature review of current handover work related to hybrid networks. This review provides valuable insights into the existing solutions for seamless handovers in hybrid networks and identifies the gaps that still need to be addressed. Additionally, we propose a robust handover mechanism for hybrid VLC/WiFi networks, which we analyze in our testbed. Our solution considers both horizontal and vertical handovers. Secondly, we verify the effectiveness of our proposal by implementing it in our testbed. We gather user mobility data using the doppler velocity element and utilize both VLC and WiFi networks to make the most accurate handover decision. Finally, we apply fuzzy logic and machine learning algorithms to our testbed, further improving the performance of the handover mechanism.

The paper is organized as follows. In Section II, we provide an up-to-date literature review of the latest handover algorithm for the hybrid system model. Section III outlines our proposed handover mechanism, specifically designed to optimize performance in our testbed environment and applicable to other similar hybrid systems. In Section IV, we present the results of our experiments and provide a performance evaluation of our proposed handover mechanism.

II. LITERATURE REVIEW

TABLE I. SUMMARY OF THE LITERATURE REVIEW

Ref	Outcome	Remark
[1]	Considered mobility in VLC and HO based on RSI in both overlap and non-overlap coverage	Simulation, HHO
[2]	A novel handover skipping scheme based on reference signal received power (RSRP) and their changed rate to determine the handover target.	Simulation, HHO
[3]	Proposed HO considers a handover skipping scheme and aims to tackle the negative impact of the handover rate	Simulation, HHO
[4]	Handover based on RSSI and studied handover probability based on a Markov chain model.	Simulation, VHO
[5]	A Markov decision process adopts a dynamic approach to obtain a trade-off between the switching cost and the delay features.	Simulation, VHO
[6]	Fuzzy logic (FL) algorithm with dynamic handover scheme for dynamic HO. Channel state information, user speed and desired data rate are considered.	Simulation, VHO and HHO
[7]	Adopts a dynamic coefficient via machine learning. Adaptive handover mechanism and selection algorithm optimization are the main focus.	Simulation, VHO and HHO
[8]	HO is based on link aggregation and MPTCP tools. The main focus is lower handover outage duration and a high network throughput.	Experiments, VHO and HHO

In a hybrid network, horizontal and vertical handovers are the two main types of handovers. Horizontal handover (HHO) occurs within the domain of a single technology, while vertical handover (VHO) occurs between different wireless access technologies. During a VHO, the air interface is modified while keeping the destination's path constant. There are mainly three types of research related to handovers in a hybrid network: i) HHO in VLC, which focuses on improving performance within the VLC domain; ii) VHO between VLC and WiFi, which aims to optimize handovers between these two wireless access technologies; and iii) studies that work on both VHO and HHO, providing a more comprehensive approach to addressing handover challenges in hybrid networks.

Handover metrics are critical in determining when, where, and how to perform handovers in a hybrid network. To ensure seamless user connectivity, various quality of service elements that impact handover must be considered. For example, factors like RSSI, CSI, network load, handover delay/latency, user preferences, and so are all essential considerations. The duration of handovers can also vary depending on the type of handover. However, minimizing handover time is crucial to prevent disruption to user services, and therefore, choosing between HHO and VHO is vital for the hybrid system. Overall, effective handover mechanisms should consider multiple factors, including QoS elements, handover duration, and user preferences. In this paper, we have presented the most recent handover mechanisms for hybrid systems. However, it is worth noting that previous studies on HHO or VHO are also relevant to our work and can be found in reference [9]. Many of them lack implementation, which is crucial for verifying their effectiveness in a testbed environment. To address this gap, we have developed and implemented our handover mechanism in an open platform. By doing so, we can verify the effectiveness of our proposed handover mechanism in a real-world setting and ensure that it provides superior performance compared to existing solutions.

III. PROPOSED METHOD

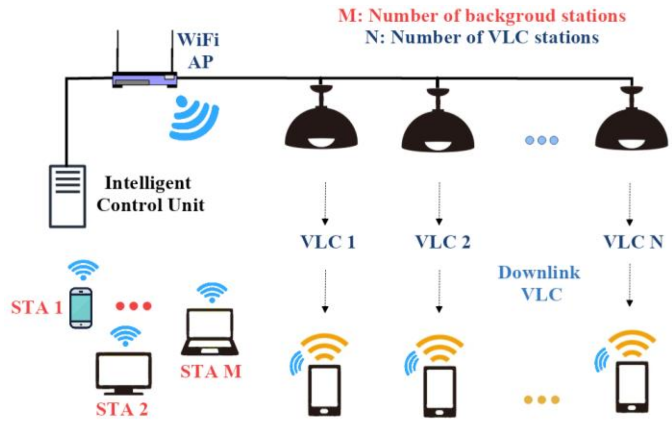

Fig. 1. Simple scenarios for hybrid VLC/WiFI network

Handover management is a critical aspect of developing solutions and supporting mobility scenarios. It is the process by which the user maintains its active connection while moving from one point of attachment to another. This section describes the handover process features and provides the handover decision problem in a heterogeneous network. The handover scenarios which we consider are shown in Fig. 1.

Many works describe the handover process in three phases. Firstly, handover information gathering refers to the process of collecting all the essential information needed to identify when a handover is necessary and to initiate it if required. This phase is also known as the handover initiation or system discovery phase. By gathering critical information, such as signal strength and available bandwidth, this phase helps determine when a handover is necessary and triggers the subsequent steps in the handover process. Secondly, the handover decision phase is responsible for determining whether and how a handover should be performed. This involves selecting the most appropriate access network based on specific criteria, such as user preferences, and providing instructions for the execution phase. Also known as network or system selection, this phase is crucial in ensuring a seamless and efficient handover process. By making informed decisions about which network to connect to next, the handover process can help maximize network performance while minimizing disruptions to the user experience. Thirdly, the handover execution phase involves changing channels in accordance with the details determined during the decision-making phase. Once the appropriate access network has been selected, this phase takes action to execute the handover, ensuring that the user's connection is smoothly transferred from one base station or access router to another. By performing the handover promptly and effectively, this phase helps maintain continuous connectivity for users as they move across different attachment points.

A. Handover Information Gathering in VLC

Handover decision criteria help to determine which access network should be chosen, and the handover decision policy represents the influence of the network on when and where the handover occurs. We plan to use RSSI values for traditional handover decision policy because this is the most effective and does not require further information to learn about VLC channel conditions. The technique compares the old RSSI (*oRSSI*) and the new RSSI (*nRSSI*). There are four different policies that can be employed based on these values. i) RSSI value if *nRSSI* > *oRSSI; ii)* RSSI with a threshold (*thr)*: choosing the new BS if *nRSSI* > *oRSSI* and *oRSSI* < *thr*; iii) RSSI with a hysteresis (*h*): choosing the new BS if *nRSSI* > *oRSSI* + *h*; iv) RSSI with both hysteresis and threshold: choosing the new BS if *nRSSI* > *oRSSI* + *h* and *oRSSI* < *thr*.

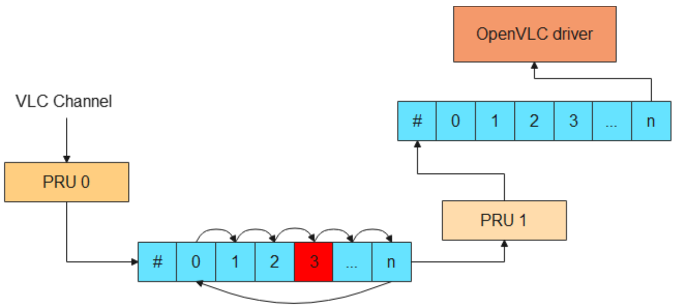

Fig. 2. Memory sharing between PRUs and OpenVLC driver receiver

Our testbed is built on OpenVLC 1.3, an open platform that enables researchers to develop their prototypes [10]. The OpenVLC system comprises three components: the OpenVLC cape, which is the front-end transceiver connected to the Beaglebone Black; the OpenVLC firmware, which runs on the Processing Real-time Units (PRUs) that function as microprocessors for the BBB and performs real-time processing; and the OpenVLC driver, which is a module in the Linux kernel that implements the VLC MAC and PHY layers, as well as sampling, symbol identification, coding/decoding, and Internet protocol interoperability. However, the current state of the OpenVLC platform does not provide RSSI to a Linux environment. The OpenVLC firmware stores each of the 16 bits of the current RSSI value in the register of PRU0. Once read, this RSSI is compared with a threshold for decoding. After decoded, a new RSSI value is started to be read, so the previous one is lost. The process shows in Fig. 2.

To extract the RSSI value and integrate it into our handover mechanism, we utilized a prudebug-bbb tool to gain insight into the registers used by the OpenVLC firmware. With this knowledge, we modified the firmware to search for the register containing the RSSI value. Our efforts led us to identify *r3* as the essential register for storing the RSSI value from PRU0. By successfully retrieving the RSSI value on the receiver side, we have taken a significant step toward implementing our handover mechanism.

B. Handover Information Gathering in WiFi

We utilize a commercial USB dongle to establish a WiFi channel link in a hybrid system that facilitates testbed replication for fellow researchers. It is crucial to ensure the compatibility of selected dongles with the system and that they meet the necessary performance requirements. Moreover, documenting the configuration process of the dongle and WiFi channel setup could assist other researchers in following the protocol quickly. Our investigation of WiFi channels relied on a diverse set of tools, with particular emphasis on extracting CSI information. In addition to discerning link quality and data rate metrics, we are particularly interested in utilizing CSI information to gain insights into user mobility patterns. As prior studies suggest, doppler velocity information derived from CSI measurements can provide excellent approximations of the user's movement speed [11].

IV. Experiments Results

A. Hybrid VLC/WiFi testbed

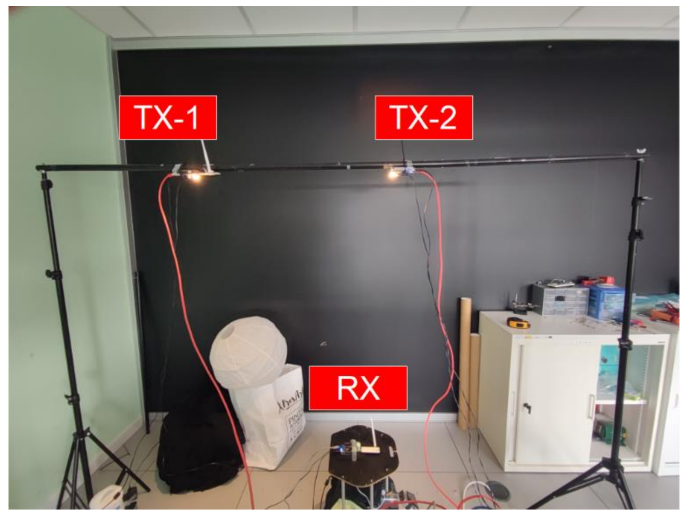

Fig. 3. Experiment setup for hybrid VLC/WiFi testbed

Our testbed includes two OpenVLC transmitters with WiFi integration, which enable efficient data transmission over visible light. On the receiver side, we have one OpenVLC unit with customized firmware, which is mounted on a robot that can move freely between the two access points. One critical feature of the VLC channel condition is the RSSI value, which measures the signal strength between the transmitter and receiver. To better understand this aspect of the OpenVLC platform, we conducted experiments to observe how the RSSI value changes as the receiver moves further away from the center point of the OpenVLC AP. With all knowledge about OpenVLC, we successfully retrieved the RSSI value on the receiver side, enabling us to integrate it into our handover mechanism, which determines the most effective base station for seamless handover. By conducting experiments to monitor the RSSI value as the receiver moved away from the center point of the OpenVLC AP, we gained insight into the performance of the VLC channel under different conditions. Our results showed that the maximum RSSI value decreased as the receiver moved further away from the center point, indicating a degradation in signal strength like in Fig. 4. These observations may also lead to advancements in the performance of VLC systems, as a better understanding of channel conditions can result in more robust systems that deliver higher data rates and improved reliability.

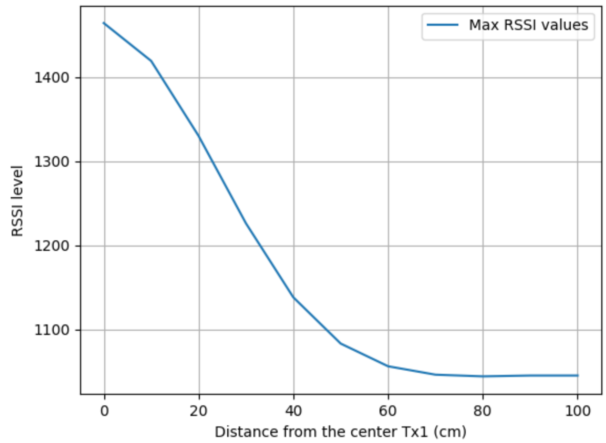

Fig. 4. The maximum RSSI values capture the different distances between center point OpenVLC Tx and OpenVLC Rx.

After careful consideration, we used the sample standard deviation of RSSI values (*sRSSI*) to measure RSSI channel variability. We chose *sRSSI* because it provides a comprehensive view of the RSSI channel and is less prone to bias than other standard deviation estimates. Overestimating variability in samples is preferable to underestimating it, which could potentially lead to inaccurate results. Therefore, *sRSSI* is a reliable way to gauge RSSI variation in our study.

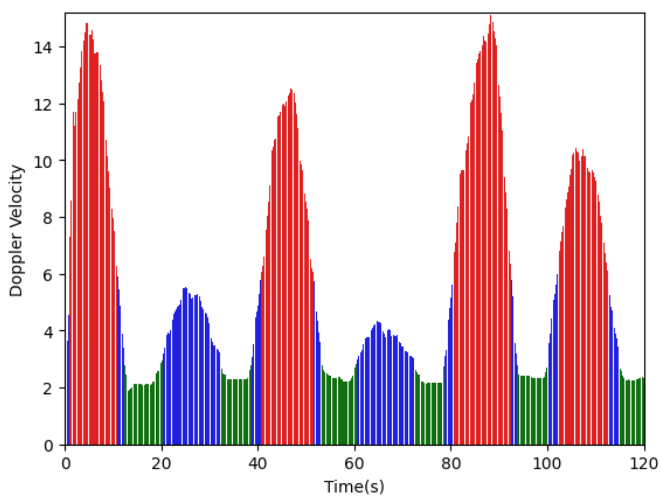

Fig. 5. Doppler velocity envelope extracted from a testbed scenario.

To investigate user mobility in a WiFi environment, we collected CSI data and extracted doppler velocity components, as depicted in Fig. 5. The experimental setup involved linear movements of a receiver at different velocities. The sequence is the receiver moves at high speeds for the first 10 seconds, followed by a slow movement for the next 10 seconds, with a 10-second pause in between. This cycle was repeated for 120 seconds. Our analysis revealed a strong correlation between the doppler velocity and the rate of user mobility, allowing us to categorize it into three levels based on our predetermined thresholds: slow movement (green), medium movement (blue), and fast movement (red). We plan to leverage this information in our machine learning algorithms, which we will elaborate on in the subsequent section in Fig. 5.

B. *Handover Decision.*

Handover decisions are crucial in the handover process, especially when developing a handover mechanism between VLC and WiFi networks. However, this can be challenging due to differences in physical layers, communication protocols, and network architectures. Therefore, selecting appropriate handover criteria is of utmost importance. In our study, we experimented with various combinations of techniques and features that can be collected from both networks. After careful consideration, we decided to employ fuzzy logic for our small-scale testbed, which allowed us to achieve fast handover times while meeting our requirements.

TABLE II. FUZZY LOGIC RULES

Rule No.	Features			AP Allocation
	sRSSI 1	***sRSSI 2***	***WiFi data rate***	
1	*not* Low	-	-	VLC1
2	-	*not* Low	-	VLC2
3	Low	High	-	VLC2
4	High	Low	-	VLC1
5	Low	Low	not Low	WiFi

In our fuzzy logic approach, we consider the *sRSSI 1* and *sRSSI 2* values for two OpenVLC access points, respectively. We choose the WiFi data rate as the most convenient feature to learn about WiFi channel conditions. In our testbed, in case the VLC channel is appropriate for transmitting data, we prioritize it over the WiFi channel, which serves as a backup network. This approach helps reduce the likelihood of bottleneck issues in the WiFi channel [12][13]. In our OpenVLC platform, the maximum achievable data rate is 400 kbps. We observed that when sRSSI is low, traffic drops below 50 kbps, which led us to define the sRSSI threshold at this level as a handover procedure that should take place. We demonstrate the fuzzy logic rules in Table II.

C. *Handover Execution*

As part of our experimental study, we conducted tests in several indoor environments to evaluate the effectiveness of our proposed hybrid handover solution. We collected data for five minutes while the receiver moved in the same cycle as we collected CSI data for doppler velocity. These tests assessed the system's ability to handle handovers seamlessly between VLC and WiFi networks. Our experiments generated valuable data, presented in Table III, which showcases the minimum and maximum handover times for HHO and VHO. As predicted, the experimental results indicate that the handover time for VHO is typically more than double compared to the handover time in HHO. For HHO, the minimum handover time observed ranges from 0.043 s to 0.105 s, while for VHO, it ranges from 0.286 s to 0.431 s. Although the handover time has not yet been defined in VLC standardization, these results meet the standard for handover time in other radio frequency technologies.

TABLE III. HANDOVER TIMES

Handover type	Handover time	
	Minimum (s)	***Maximum (s)***
Horizontal	0.043	0.105
Vertical	0.286	0.431

Our results demonstrate better performance than the latest reported handover time for the Li-Wi network in [8] that we discuss in section II. In that study, the author employed MPTCP and link aggregation tools to develop handover mechanisms, only achieving a minimum handover time of 0.2 s to 0.35 s.

D. Handover with User Mobility and Machine Learning

Our experiment aims to scale up our operations in a massive IoT system by utilizing machine learning techniques to develop robust handover systems. Gathering more information about our testbed is crucial before fine-tuning the machine learning model. Moreover, our approach prioritizes decisions based on maintaining a minimum throughput, which guarantees that the quality of service remains consistently high across all user scenarios and movement patterns. To achieve this, we have identified six features - maximum RSSI, minimum RSSI, *sRSSI*, WiFi link quality, WiFi noise level, and WiFi data rate - that can provide valuable insights into network performance. In addition, we have incorporated user mobility as an essential feature by extracting it from doppler velocity data. This information has been categorized into three distinct movement patterns - slow, medium, and fast - as illustrated in Fig. 5. By integrating user mobility data with other relevant features, we aim to improve the accuracy and reliability of our machine learning model for predicting handovers in different scenarios.

TABLE IV. PERFORMANCE OF CLASSIFIERS

Classifier	Training Size (%)	Accuracy (%)	Ave. Training Time (s)
KNN	40	85.4	0.01
	60	90.5	
	80	93.1	
Random Forest	40	87.6	0.08
	60	90.3	
	80	95.3	
AdaBoost C4.5	40	87.2	0.03
	60	90.1	
	80	97.5	
LMT	40	86.2	0.05
	60	90.5	
	80	93.1	

To identify the most effective algorithms for improving our machine learning model, we experimented with several supervised learning techniques, including Logistic Regression, Support Vector Machine Classifier, Gradient Boosting, Naive Bayes Classifier, and others. Based on our initial analysis, we selected the four methods that displayed the greatest potential for enhancing the accuracy of our model while requiring a fast-training time. These techniques were K-Nearest Neighbors, Random Forest, AdaBoost C4.5, and Logistic Model Tree. We proceeded to fine-tune these models and evaluated their accuracy results, which are presented in TABLE IV.

Our analysis indicates that when 80% of our dataset is used to train the model, the accuracy of predicting handovers exceeds 93%. During the tuning process, we found that the AdaBoost C4.5 algorithm displayed the most significant potential with an impressive 97.5% accuracy. We selected AdaBoost.C4.5 because it employs Decision Trees as its base classifiers, which are widely recognized for their effectiveness in machine learning applications. Specifically, AdaBoost.C4.5 incorporates the C4.5 decision tree algorithm into the AdaBoost framework. Unlike AdaBoost, which uses weak learners, AdaBoost.C4.5 builds a forest of decision trees and selects the best one to add to the ensemble at each iteration. This approach allows AdaBoost.C4.5 to identify more complex relationships in the data than AdaBoost alone, leading to improved predictive accuracy.

Our machine learning model for the handover system was optimized by utilizing two essential hyperparameters, namely *n_estimators* and *learning_rate*. The hyperparameter *n_estimators* was set to 100 and 200, indicating the maximum number of estimators utilized before the AdaBoost.C4.5 algorithm terminated the boosting process. By increasing this value from the default 50, we could reduce the model's variance while preventing overfitting on the training data. Furthermore, we could determine the number of expanding rounds executed before the algorithm stops by utilizing *n_estimators*. The second hyperparameter, *learning_rate*, was tuned from 0.001 to 0.5. This parameter controls the weight update during each iteration of the boosting process. A lower value of *learning_rate* leads to a slower adaptation of the model to the gradient of the loss function, while a higher value results in a faster adaptation. It is crucial to strike a balance between the two hyperparameters since using a small *learning_rate* and many estimators might not lead to better results and can increase computational costs.

In conclusion, selecting appropriate values for these hyperparameters is paramount in influencing the model's performance. As such, we paid keen attention to tuning both hyperparameters to strike a balance between model accuracy and computational efficiency. There is potential to expand this research further by incorporating more transmitter and receiver access points with different hybrid VLC and RF technology. Additionally, we can further boost the performance of our machine learning models by increasing the size of the data available through the hybrid system.

V. CONCLUSIONS

Developing a seamless handover mechanism between the two systems is crucial to explore VLC and WiFi integration’s full potential. Our proposed testbed serves as a platform for researchers to address the challenges associated with handover mechanisms and develop more efficient, reliable, and secure communication systems across different industries and applications. To achieve seamless integration between VLC and WiFi systems, we proposed a hybrid handover solution based on RSSI and CSI values for both HHO and VHO. Our experimental results indicate that the proposed solution achieves maximum handover times of around 100 ms and 400 ms for HHO and

VHO, respectively. Additionally, our machine learning algorithm for handover decision-making provides remarkable accuracy, with a score of 97.5%. The results demonstrate that our proposed solution can achieve efficient handover times in diverse indoor environments. This underscores the importance of developing a seamless handover mechanism to enable other researchers working on hybrid systems to implement their work in a similar testbed environment.

In the future, several extension ideas warrant further investigation. Integration of tracking and localization into our machine learning model could lead to more efficient handovers by dynamically adapting to user movement patterns and changing network conditions. Developing an architectural solution for managing strip-LED systems allows seamless communication with multiple receivers and traffic flows while balancing the complexity of individual LED intelligence modules. Exploring resource allocation trade-offs between traffic load in each cell and dwell time during handovers may optimize overall system performance. Additionally, investigating adaptive node-association strategies based on anticipated user movement could minimize handover dwell times, even in cell-free systems. By pursuing these research directions, we aim to enhance the applicability and efficiency of our proposed handover mechanism, ultimately contributing to improved user experiences and more robust large-scale networks.

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