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RESEARCH ARTICLE

Card-Flipping Decision-Making Technique for Handover Skipping and Access Point Assignment: A Novel Approach for Hybrid LiFi Networks

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ABSTRACT The hybrid LiFi/WiFi communication networks have demonstrated their efficacy and advantages in terms of data transmission rates. Multiple difficulties were identified in these networks, including the access point assignment (APA) and the process of handover (HO). These troubles (criteria) are influenced by multiple elements, including optical gain at the recipient, mobility, distance, blockage, shadowing, and other variables. It is crucial to evaluate multiple criteria when making-decisions in order to attain more precise results. However, as far, limited studies employing the multicriteria decision-making (MCDM) technique for a hybrid LiFi/WiFi network has been discovered. Nevertheless, although the MCDM technique is highly accurate, it involves long process to achieve the optimal access point (AP). This results in heightened complexity of the system, leading to longer AP transfer times and higher HO rates. In order to address the aforementioned constraints, this paper introduces a novel approach termed as card-flipping decision making (CFDM). CFDM enables swift and precise decision-making while minimizing computational complexity. Additionally, it incorporates HO rates that involve bypassing HOs and selecting the most optimal AP. The analytic hierarchy process (AHP) is adopted to estimate the subjective weights of each criterion and establish their level of priority. The proposed method provided in this study is combined with the AHP, referred to as the merged AHP-CFDM. This integration is considered a new MCDM technique. The proposed method consists of an algorithm that performs i) criteria segmentation based on criteria values, ii) criteria sortation based on AHP results, and iii) criteria grouping based on network type. The classification of criteria is also taken into account including cost and benefit criteria. The proposed algorithm treats each criterion as a card, and each card is flipped (computed) when necessary. The outcome of the AHP-CFDM decisions are SKIP, FLIP, and ASSIGN. The proposed AHP-CFDM is a new MCDM technique and can be utilized in other networks and/or applications for decision-making. The investigation demonstrates improvements in total system efficiency in terms of computational complexity and HO rates when compared to both standard approaches and benchmark techniques. The simulation results demonstrate that the proposed strategy outperforms other methods significantly when compared to the most relevant studies.

INDEX TERMS LiFi, hybrid network, decision making, handover, access point assignment.

I. INTRODUCTION

The 2020 statistical analysis showed that mobile data transmission made up 71% of Internet traffic and over 80% of data transmission in indoor locations like homes and offices [1]. In addition to increased cellular technology use

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during crises and pandemics [2], [3]. LiFi technology supports radio frequency (RF) spectrum limitation management since it makes use of a broad spectrum of visible light as a carrier (approximately 300 THz) and is capable of transmission rates above 10 Gbps [4]. Light blocking and coverage area limitations plague LiFi networks despite their high data transmission speed. Due to WiFi network availability, carrier route blocking was reduced. Converged WiFi and LiFi networks offer tremendous coverage and rapid data transfer [4], [5].

LiFi/WiFi hybrids use WiFi's wide coverage and LiFi's quick data delivery. Recently, researchers have focused on the hybrid LiFi networks, which combine WiFi and LiFi [6], [7]. This network has the potential to vastly improve network performance compared to individual WiFi/LiFi systems.

RF systems use RF chains to convert modulated electrical signals into RF electromagnetic waves. In contrast, LiFi transmitter front-end components convert a modulated electrical signal into a light signal, while reception front-end devices convert the light signal return to the modulated electrical signal. Most low-cost incoherent LiFi front ends use intensity modulation (IM) with direct detection (DD) for downlink broadcasting, which affects the downward transmission path characteristics [8].

LiFi APs service a 2–3-m radius. Thus, mobility management concerns cause horizontal handover (HHO) within a single wireless access technology [9], where the user is moved to another AP, are inevitable. Regular HO increases connectivity interruptions, packet losses, and delays, causing a poor user experience. HOs in LiFi networks are also caused by light-path occlusion [10].

To address the issues highlighted above, hybrid LiFi and WiFi networks were created to combine LiFi's high data rate and WiFi's widespread coverage [11]. This hybrid system uses vertical handover (VHO) between wireless access protocols like WiFi and LiFi, or vice versa. Due to differing media access control pathways, VHOs delay more than HHOs [12]. Thus, frequent VHOs would greatly reduce system capacity. A VHO process has three modules: metric gathering, decision-making, and HO execution. The most important stage is decision-making, or the HO algorithm. After selecting a mathematical tool to model the VHO problem, the method must be simulated to evaluate its performance.

Hybrid networks can improve network performance, but user mobility complicates load balancing (LB) and HO considerations. Because WiFi APs have a greater coverage area but lower capacity than LiFi APs [13]. The LiFi AP's coverage region is called "Attocell". When LiFi attocells collide, optical co-channel interference (CCI) occurs. LiFi attocells represent the service area, where users connect. However, attocell size and illumination depend on the distance between the AP transmitter and receiver, room height, and optical energy transfer.

A hybrid LiFi and WiFi network usually causes APA issues and users may confront HO even when inside the cell due to LiFi AP data rate fluctuations, optical gain, RF data rate shifts, and WiFi AP predominately attracting users right next to it, resulting in inefficient use of nearby LiFi APs. LiFi AP users must reside in HO circles. When a HO circle does not overlap with other attocells, LiFi AP users do not experience optical CCI. Any adjacent LiFi APs should be further away than LiFi attocell diameter to avoid optical conflict. If the link recovers before the dwell length, the mobile user will stay in optical networks; otherwise, the HO to the RF network will be done. Due to optical signal line-of-sight (LOS) propagation and ultra-dense LiFi access point deployment, the HO problem becomes difficult to solve and a HO scheme that adapts to complicated interior working circumstances is difficult to build.

As detailed in the following section, LB, APS, HHO, and VHO have been extensively researched to address these difficulties. If the user is traveling along the edge of a low-tier AP coverage zone, a mobile user may encounter frequent HO, which reduces throughput and user service quality. Moving the UE to a higher-tier AP with greater coverage can reduce HO.

A. MOTIVATION

In order to leverage the APA and HO processes in hybrid LiFi networks, it is important to consider multicriteria in addition to specific details within the process.

The multicriteria decision-making (MCDM) method [14], [15], and problem for APA in hybrid LiFi/WiFi networks have only been studied once [14]. The MCDM approach prioritized weighing, analyzing, ranking, and prioritizing all criteria. The work was accurate, although it contains several stages and mathematics. Thus, more steps and superior algorithms will result in greater computing complexity, delaying the HO process and data transfer. This could also affect the decision in the APA for selecting the best AP as well as the HO process which could lead to increased HO rates.

Additionally, [15] proposed an adaptive cross-layer HO algorithm based on multipath transmission control protocol (MPTCP) for hybrid LiFi and WiFi networks to address the HO issue by offering a movement index system based on the fuzzy analytic hierarchy process (FAHP) and technique for order preference by similarity to the ideal solution (TOPSIS) to define the mobility of users. The MPTCP-based adaptive cross-layer HO method provides cross-layer help between the physical, data connection, and transport layers. Only the mobility score was determined by AHP and TOPSIS, while the algorithm made the judgments.

The research [16] also showed that hybrid LiFi/WiFi networks can readily overwhelm algorithms because LiFi and WiFi coverage regions overlap. Additionally, researchers must find simple approaches to assure QoS with low complexity.

Rate maximization was examined by optimizing constellation dispersion and power allocation [17]. They design a framework that maximizes the lower bound of the possible rate to balance computational complexity and transmission performance. Furthermore, the study [18] introduced a novel, precise, low-complexity LiFi channel modeling approach for realistic indoor situations. Another innovation was simulating the LOS and beginning reflections exactly in the frequency-domain through a well-established mathematical model based on the integrating sphere for all higher-order diffuse reflections, which simplified channel design. This research illustrates that dense LiFi network channel modeling may be simplified and yield computationally efficient, exact, and realistic results. However, the prior efforts only considered computational complexity in a limited manner, designing a phase or a few phases for hybrid LiFi networks. All associated research will be detailed in the next section.

There has been no study on multi-criteria decision making for APA and/or HO in hybrid LiFi networks with reduced complexity. In hybrid LiFi/WiFi networks, there are no strategies that evaluate several criteria for DM and a strategy for computational complexity reduction and speedy decision making for APS and HO, which motivated this study.

B. CONTRIBUTION

This paper proposes a new technique called CFDM to improve the number of HOs and the APA process for connected users with faster decisions and reduced calculation complexity to ensure an uninterrupted connection for all users with decreased HO rates, rapid decision, and optimal rate. The method involves the CFDM algorithm.

The proposed method examines criteria-related steps before performing the algorithm. The AHP method is adopted to determine each criterion's subjective weight and experts' judgment of its value. Finding the AHP process's weights involved CR and AHP consensus indicator calculations utilizing RGMM and Shannon entropy. Thus, criteria for the proposed algorithm are prioritized. Double standards apply to the APS and HO, with one set of principles/factors applying more strictly to one group of users or circumstances. This is typically used to describe decisions that favor one group over another. When two or more users or events are handled differently when they should be, a double standard occurs. This is because HO triggers may differ from APS triggers [7], [10], [11], [19], [20].

The proposed method takes into account multiple criteria, and a novel concept will be proposed in this study. This CFDM technique consists of multiple phases and executes each phase separately. This method performs rapid decisions, which are represented by executing one phase and/or more and then skipping other phases where applicable. Our new method consists of an algorithm that is designed for selecting better AP, reducing HO rates, and reducing the computational complexity (floating-point operations (FLOPS)) with the privilege of using multicriteria, criteria weighting, and criteria prioritization. Mathematical expressions are derived to analyze the performance of the proposed method by simulations using the MATLAB software. The main contributions of this paper are summarized as follows:

- A first of its kind AP selection and HO management technique for hybrid WiFi and LiFi networks is proposed while considering multicriteria called card-flipping decision making (CFDM).
- System-model formulation and a novel integration of the proposed algorithm with the AHP method are presented.
- Simulation-based evaluation has been performed using MATLAB software for evaluating the proposed algorithm, including HO rates, and computational complexity (FLOPS).
- The proposed integrated AHP-CFDM technique is compared against previous methods, including FL-based DM, and the MCDM method.

C. ORGANIZATION

The paper is organized as follows: Section I shows the introduction, including background, motivation, contribution, and outline. Section II explains the related works and research gap in details. Section III explains the methodology, including system setup, channel models, and the proposed scheme. Results and discussion are given in Section IV. Finally, the conclusion of this work follows in Section V. All the abbreviations used in this study are listed in Appendix.

II. RELATED WORKS AND RESEARCH GAP

HO management and APS strategies and the effects of increased processing complexity in prior efforts are addressed in this section. Additionally, an overview of relevant studies shows comparisons and differences, as well as their features and qualities. This section includes a summary and investigations into the gap along with associated works.

This section categorizes all hybrid LiFi network studies in AP assignment, AP selection, HO management, HO skipping, and LB. The first group covers DM and fuzzy logic (FL) investigations. All typical schemes and algorithms that use mathematics and/or equations to achieve their goal are in the second group. Figure 1 shows the classification of the studies.

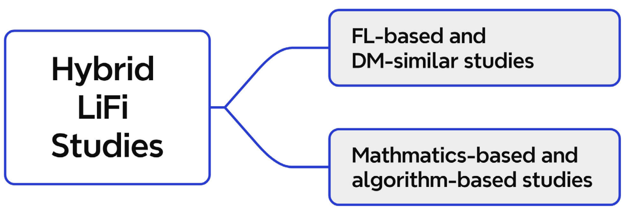


FIGURE 1. Literature review classification.

A. FIRST GROUP: FL-BASED AND DM-SIMILAR STUDIES

Criterion variables, including network capacity, blockage level, user speed, and others, might affect the APA process. Some recent research studies have used these characteristics as "evaluation criteria" instead of conditional APA techniques.

Using these criteria can improve the APA process and QoS by providing more accurate results. The diversity of criteria, their conflict, weights (importance), and priorities are also significant while addressing multi-criteria decisions. Additionally, evaluating the criterion equally may produce erroneous results. Thus, to resolve this issue, each criterion must be examined in relation to the APA process.

The MCDM approach has been applied in many fields such as blockchain [21], mobile crowd computing [22], and fuzzy logic [23]. In addition, the study [24] proposed an analysis of research on multiple criteria decision making with emphasis on the energy sector. The multicriteria decision analysis (MCDA) method was used to solve oil and gas decommissioning problems in [25]. The study [26] presented a decision-analysis-based approach that quantifies threat, vulnerability, and consequences through a set of criteria designed to assess the overall utility of cybersecurity management alternatives. Moreover, the study [27] presented a literature from 1960 to 2019 of multicriteria decision analysis in the healthcare sector.

In addition to various fields and topics, the MCDM approach was used in wireless networks. In [14], a network-level user selection MCDM problem was created. Choosing the AP network from several possibilities is an MCDM problem, and the decision problem was characterized as a hierarchy of simple and small subproblems. A hybrid LiFi/WiFi network user APA framework employing MCDM was proposed in this paper. The AHP was used to determine each criterion's subjective weight and experts' judgment of its value. Considerations for AHP weights included the CR and the AHP consensus indicator, derived using RGMM and Shannon entropy. The VIekriteri-Jumsko KOmpromisno Rangiranje (VIKOR) approach was used to choose the best AP for users, whether LiFi or WiFi. Using weighted criteria simultaneously, the integrated AHP–VIKOR solved the APA best. Beyond their findings, their criterion analysis can be used to generate new methodologies for APA and/or HO approaches.

A FL-based APS approach with near-optimal performance and low computational cost was suggested [28]. However, rule-based methods are less adaptive to network setup changes. To decide who gets WiFi access, they used FL. Second, the remaining users were connected to LiFi to increase throughput and simplify the system. Despite reduced processing energy, the FL-LB was more sophisticated than the FL-SSS.

Another FL-based dynamic HO technique was suggested in [29]. This FL approach determines HO prompting based on channel state information (CSI), user speed, and desired data rate. The FL approach can employ a tremendous deal of input data (e.g., instantaneous, and average CSI, user speed, and needed data rate) to find a low-complex load-balancing strategy to increase system throughput.

Another study [30] offered a combined optimization problem for user network-level choice. The unique FL-based technique described here can prevent user mobility and light-path obstructions, which make load balancing harder. FL-based algorithms were proposed to narrow the optimization problem's search range to reduce computational complexity. The algorithm's optimality and computing complexity were calculated. The suggested method assigns network access to each user based on cell dwell time (CDT) and obstruction data. The suggested method does not require instantaneous channel state information; hence, it requires fewer updates than existing methods.

In [31], FL and fuzzy rule-based artificial neural network (ANN) HO decision algorithms were presented. The FL-based HO algorithm determines whether to urge HO based on the instantaneous signal-to-interference-plus-noise ratio (SINR), the received signal strength (RSS), average SINR, and user velocity. However, increasing input parameters and fuzzy rules increases computational complexity, which dramatically impacts the FL system.

B. SECOND GROUP: MATHEMATIC-BASED AND ALGORITHMS STUDIES

The study [32] examined AP selection and mobility-aware load balancing. It creates a hybrid LiFi network mobility-aware LB utilizing mobility aware LB using the Kho–Kho optimization algorithm (MALB-KKOA). The technique's ability to have multiple AP associations (MA) and one AP association (SA) is examined. In the SA phase, an AP helps each client and assigns them to a network to reduce HO. However, MA does not involve VHO. The methodology is also based on Kho–Kho tag-team playing strategies. It minimizes packet loss and delay with an objective function.

In hybrid LiFi/WiFi networks, [15] suggested an adaptive cross-layer HO algorithm based on MPTCP. To provide a seamless HO, the system can adapt to the user's trade type and behavior. The user mobility index (MI) was defined by nine evaluation indicators that consider three aspects of real-time network properties, user mobility characteristics, and network service requests. The user's mobile score is calculated using the FAHP and TOPSIS to analyze the three categories of indicators. MI and SINR can dynamically set HO margin (HOM) and time to trigger (TTT) for load balancing.

AP information value model (IVM) and intelligent HO model (IHM) are first established in underground LiFi networks [33]. IVM can forecast user access to each AP. The IHM is then built by extensively analyzing the handhold alternating obstruction problem based on this likelihood. Due to more mixed states, this model needs more samples. In particular, the combination of components was ignored. No doubt, this will influence prediction accuracy. When components are independent, the combination of factors provides the same information as each element individually. The information value influenced by numerous factors is an equal-weight superposition. Area selection-controlling factors are reduced. But it's also a fix-weight superposition. Each factor's influence may vary at different times, which was ignored.

A realistic LiFi channel can be modeled using machine learning methods like deep learning (DL). DL's easy indirect real-time estimate procedure using the channel as a black box differs from traditional methods. Instead of directly measuring useful channel information like channel gain, received signal-to-noise ratio (SNR), bit error rate (BER), etc., the DL model can learn it from the environment and user behavioral data to account for the geometry.

The authors [34] created a machine learning-based seamless VHO technique for LiFi/WiFi hybrid networks. The program forecasts the number of time intervals for blockage in the next time period. Using this forecast, this system proactively conducts VHO by trading off average available data rate (AADR) and service interruption.

Increased end-device resources allow APA to make client-side decisions. Energy efficiency is also important due to client-side power limits.

The study [35] proposes client-side energy-efficient AP selection for hybrid WiFi/LiFi QoS provisioning. The proposed method, complexity and convergence assessments, simulation-based evaluation, and uplink transmission power adaptation study were presented in this work. The results demonstrate that next-generation networks could use the given technique for QoS provisioning and energy efficiency. Clients understand their QoS, application, and device requirements, and channel circumstances better. Distributed techniques reduce the demand for signaling information for AP selection and promote network scalability by relieving network devices.

LOS propagation of the optical signal makes the HO decision-making challenge more essential and difficult than in heterogeneous networks. In [36], ANN-based HO schemes were proposed for the binary classification HO decision-making problem. The whole HO strategy uses two sets of ANNs to make HO judgments using channel quality, user movement, and device orientation. The HO mechanism that provides decision-making rules is most crucial in HO scheme design. The HO algorithm is a multiple-input single-output function, with inputs being the values of all metrics utilized for decision-making and outputs being "0" or "1", indicating the decision outcome. HO algorithms can be developed with any mathematical technique that approximates these functions.

A link aggregation (LA) network needs effective load balancing to maximize efficiency. A progressive load balancing strategy with reinforcement learning (RL)-based APA and optimum resource allocation for LA-enabled hybrid LiFi networks was suggested [37]. With its minimal complexity, the proposed approach performs similarly to an exhaustive search. The durability of the suggested method is also demonstrated by analyzing two user mobility models: orientation-based random way point (ORWP) and hotspot ORWP (HORWP). On the other side, the study [16] contrasted LA enabled networks with typical indoor access networks, including hybrid LiFi-WiFi, solo WiFi, and standalone LiFi using a LA-SINR algorithm.

Load balancing tactics greatly impact hybrid LiFi network performance. Since hybrid LiFi network load balancing is a nonconvex mixed-integer nonlinear programming optimization problem, it is theoretically intractable, hence, traditional optimization methods cannot provide an optimal global solution. Exhaustive search can find an ideal solution, but it's computationally expensive. Thus, the study [38] investigated a low-complexity RL-based load balancing method. HO overhead and receiver device random orientation are discussed in this article. This article introduces domain knowledge concepts to reduce algorithmic computational complexity.

QoS of LiFi/WiFi wireless networks is studied [39]. QoS-driven load balancing was examined in SA and MA. Each scenario involved an optimization challenge to minimize packet loss ratio and latency using a low-complexity iterative technique.

The suggested HO strategy in [19] is adaptable to diverse working scenarios since it gathers information about channel quality, user velocity, and arrival data rate to make HO decisions and calculate dwell values. They separated the HO problem into three subproblems by VHO category and designed a strategy for each event to achieve optimal performance with minimal complexity.

For the first time, the study [40] views HO as a pattern recognition problem to make accurate and fast decisions. This work characterized channel quality, optical channel blockage, user movement, and device orientation for a practical simulation scenario. The hybrid LiFi network's HO algorithms use two pattern recognition methods. The Gaussian kernel was their second feature mapping method to simplify calculations.

The dynamically LB system in [11] accounts for user movement and HO overhead to solve the HO problem. The study did not consider lowering HO rates; instead, it used a simple user mobility strategy using LiFi attocells for fixed users and WiFi APs for moving users. HO management and skipping affected the LB process along with user mobility. In this study, small-scale RF channel fading was ignored to simplify analysis. A constant WiFi throughput in space was chosen to simplify system throughput analysis.

Mobility-aware LB was introduced in [41] to address user mobility-related HOs. In the MT mode, feeding each user simultaneously through LiFi and WiFi avoided the VHO, hence, a joint optimization challenge was created to balance traffic demands. Despite considering obstructions, the AP user selection procedure (USP) only used the signal strength approach SSS. The USP procedure was also ignored in MT mode because the user is connected to both networks. The study advocated serving users using LiFi to conserve WiFi resources, which will boost LiFi traffic as user data rate requirements rise. This is another MT mode limitation.

Game theory was applied in [42] to adapt each user's APS strategy, improving user satisfaction at little computing cost. The work requires numerous iterations to achieve equilibrium.

Learning methods for updating AP probability distributions for APS judgments were proposed in [43]. ANN-based HO systems were also established in [44] to change LiFi and WiFi selection preferences. Traditional HO skipping techniques require user trajectory knowledge and are difficult to implement. The rate of change in reference signal received power (RSRP) can also indicate the user's movement. This research proposes an adaptive HO method that adjusts network choice based on user speed.

The RSSI user association rule does not always associate the randomly oriented UE with the nearest AP. Depending on UE orientation, LiFi AP signal strengths can be weak and unstable. Therefore, a VHO between the LiFi AP and the RF AP is necessary to keep the QoS for the users. The probability of VHO for a randomly rotating user in hybrid RF-LiFi networks was studied in [45].

Movement control in multi-tier LiFi networks using randomized geometry and the dwell time technique was also the subject of work by the authors of [46]. Taking into account received optical signal intensity (ROI), TTT, and mobility of users, closed-form formulas were developed for the cross-tier HO rate, ping-pong rate, and sojourn duration.

Because of the overwhelming demand on the network, the concept of HO skipping was developed. A novel HO skipping technique based on RSRP was proposed in the work [20], which eliminates the need for supplementary input. The method takes into account both the value and rate of change of the RSRP to get at the HO goal. However, depending on the RSRP could be disastrous due to the issue of variable and fluctuating loads on APs and interference. The research also restricted its scope to LiFi systems alone.

In [47], another HO skipping approach was added to allow HOs between two APs that are physically distant from one another. This research proposes an adaptive HO method that adjusts the user's preferred network based on the user's actual network throughput. In particular, those who are going slowly have the option of choosing the AP with the best channel quality, while those who are moving quickly are not required to leave WiFi.

The research [48] set out to examine the effectiveness of two HO algorithms, closest AP (CAP) and maximum channel gain (MCG), in a LiFi network. They examined the two HO algorithms in order to demonstrate how the orientation and motion of the UE affect the efficiency of the HO system. The first one uses the UE's proximity to four ceiling-mounted APs to determine which one will service it as it roams over the network. The strongest received signal was used to determine the maximum channel gain values in the second. The results clearly favor MCG HO decision over CAP HO decision.

Concerning user mobility and user density, the writers of [49] concentrated on APA and HO. The authors introduced a three-stage HO management and AP transition (TPHM-APT) for achieving high data rates per user and consistent connections with fewer HOs. With the goal of increasing reliability, their strategy prioritized reducing the overall number of HOs while maintaining a manageable number of users per LiFi node. Table 1 summarizes the related works, including proposed methods, problems considered, HO type, implementation, the DM and MCDM methods, and network type.

C. RESEARCH GAP AND CRITICAL ANALYSIS

Most of the above studies simplified operations using FL. Fuzzification, rule assessment, and defuzzification comprise a FL system [50]. Membership functions map single-valued arguments to fuzzy set values in the first stage. In MATLAB, membership functions (MFs) link each parameter to one of three significance levels (low, medium, or high). Fuzzy constraints are used to evaluate network access types and assignment options in step two.

Only two studies used multicriteria [14], [15]. Particularly in [14], where APA involved several procedures and details. As a typical HO, APS, and LB model has more stages, its computational complexity will increase, and system model programming will have more loops and conditions. This may degrade system responsiveness, delay HO execution, raise HO cost, and lower QoS by affecting HO and APS decision execution times and delay rates.

New models that improve system performance make the complexity challenge more urgent. Despite using multicriteria, both research [14], [15] ignored complexity. In [15], FAHP-TOPSIS was used to determine weights, and the comprehensive assessment value of the user's mobile class was used to use TOPSIS for multi-attribute decision-making, which is based on selecting the alternative with the closest Euclidean distance to the positive solution and the farthest to the negative solution. The target AP selection method adds variables like HOM, TTT, SINR, etc.

The FL approach can employ a lot of input data (e.g., immediate and average CSI, user speed, and needed data rate) to find a simple solution. However, increasing input parameters and fuzzy rules increases processing complexity, which dramatically impacts the FL system. All research that employed FL approaches to reduce complexity did so without introducing a specific function or method, relying on the FL method's clarity.

The optimization method becomes progressively more difficult as network capacity and user count rise [37]. The great complexity that comes with using exhaustive search—also known as brute force search—means that the best performance is not guaranteed. Also, a high-density network deployment would benefit the most from using a domain knowledge (DK) method [38], which simplifies the system considerably. According to the research [38], the LA enhances system performance but increases complexity.

The following Table 2 shows the limitations found in the related work regarding complexities, including steps and phases of models that could affect execution times and delays in the system.

The LA receiver system becomes more complex, making exhaustive search with LA (Exh-LA) impracticable for real-world scenarios. In [28], complexity was considered as FLOPS, while in [38], only run-time complexity

TABLE 1. Summary of related works and this study.

Ref.	Year of publication	Description	Criteria						Other factors		Problems considered				
									Others						
			Criteria evaluation	Weighted criteria	Prioritize criteria	DM	MCDM	Criteria value segmentation	Network	Implementation	HO	APS	LB	CXY	MOB
[11]	2015	LB in a mixed LiFi/WiFi network with user mobility and HO signaling overheads.	✓						LiFi/ WiFi	A & S	✓	✓	✓		✓
[14]	2023	This paper presents an MCDM-based user APA mechanism.	✓	✓	✓	✓	✓		LiFi/ WiFi	A	✓	✓			✓
[29]	2016	An FL-based dynamic HO method is proposed. This FL method determines HO prompting based on CSI, user speed, and desired data rate.	✓			✓			LiFi/RF	A & S	✓	✓	✓	✓	✓
[30]	2020	A joint optimization problem determines a network-level selection for each user over time. A FL-based approach is also presented to reduce optimization problem computational complexity.	✓			✓			LiFi/W iFi	A & S	✓	✓	✓	✓	✓
[32]	2023	MALB-KKOA is a mobility-aware LB developed utilizing the Kho–Kho optimization technique.							LiFi/ WiFi	A & S	✓	✓	✓		✓
[15]	2022	An adaptive cross-layer HO algorithm based on MPTCP is suggested to tackle the HO problem.	✓	✓	✓	✓	✓		LiFi/ WiFi	A & S	✓	✓	✓		✓
[33]	2022	AP IVM and IHM were originally established in tube LiFi networks.	✓	✓					LiFi	A & S	✓	✓			
[34]	2022	Presented an ML-based seamless VHO mechanism that anticipates the number of time intervals for blocking in the next time block.							LiFi/ WiFi	S	✓				
[35]	2022	Offers client-side energy-efficient AP selection for QoS provisioning.							WiFi and LiFi IoT	A & S		✓		✓	
[36]	2022	ANN-based HO schemes were proposed to solve the binary classification HO problem.							LiFi/ WiFi	A & S	✓				✓
[37]	2022	Introduced RL-based APA and optimum resource allocation for LA-enabled networks for sequential load balancing.							LiFi/ WiFi	A & S	✓	✓	✓	✓	✓
[38]	2022	A load-balancing algorithm based on RL is investigated. Domain knowledge has been added to reduce algorithmic computational complexity.							LiFi/ WiFi	A & S	✓	✓	✓	✓	✓
[39]	2022	QoS-driven load balancing was examined. Two optimization problems are constructed to minimize packet loss ratio and latency, and a low-complexity iterative solution was proposed.							LiFi/ WiFi	A & S		✓	✓	✓	
[19]	2022	The novel HO system divides HO occurrences into three groups and calculates the optimal stay duration for each category using a different technique.							LiFi/ WiFi	A	✓			✓	✓
[40]	2022	For the first time, they view HO as a pattern recognition problem to make correct and quick decisions.							LiFi/ WiFi	A & S	✓			✓	✓
[41]	2019	MALB methods were proposed for ST and MT scenarios.							LiFi/ WiFi	A	✓	✓	✓	✓	✓
[28]	2017	For hybrid LiFi/WiFi networks, APS was proposed in two stages. A FL system was created to identify WiFi users in the initial step. Final users are assigned in a homogenous LiFi network in the second stage.	✓			✓			LiFi/WiFi	A		✓	✓	✓	
[42]	2017	EGT-based LB was proposed to address APA and RA issues. Users with heavy obstructions can switch to RF for greater data rates.							LiFi/ RF	A & S		✓	✓	✓	
[43]	2017	Utilized an advanced multi-LED APA method. Create a multi-armed bandit model to aid LED AP selection.							LiFi/ WiFi	A & S		✓		✓	

TABLE 1. *(Continued.)* **Summary of related works and this study.**

[44]	2020	A unique ML-based HO method that adjusts LiFi and WiFi selection preference using a dynamic coefficient taught by ANN for diverse conditions.							LiFi/ WiFi	A & S	✓	✓		✓	✓
[45]	2018	A Markov chain model is used to analyse the HO probability. A robust HO algorithm incorporating threshold and hysteresis level was proposed.							LiFi/ RF	A & S	✓				
[46]	2021	This research investigates the primary-secondary cell cross-tier HO rate in a two-tier LiFi network.	✓						LiFi	A & S	✓				✓
[20]	2019	An RSRP-based HO skipping mechanism was proposed. Since RSRP changes with user velocity, the novel technique is velocity-aware.							LiFi	A & S	✓				✓
[47]	2020	Skipping HOs between non-adjacent APs was established. Low-speed users can choose the AP with the best channel quality, while fast-speed users can stay in WiFi.							LiFi/ WiFi	A & S	✓				✓
[48]	2018	This study examines HO algorithm performance in LiFi networks. The CAP and MCG HO algorithms were proposed.							LiFi	A & S	✓	✓			✓
[49]	2022	A protocol (TPHM-APT) was designed with the goal of decreasing the number of HOs, which boosts dependability and maintains low user densities on individual LiFi APs, which saves bandwidth and energy.							LiFi/WiFi	A & S	✓	✓	✓		✓
[31]	2020	Formulated FL and fuzzy rule-based ANN HO decision algorithms.	✓			✓			LiFi/ WiFi	A & S	✓	✓		✓	✓
THIS WORK		Proposed a new MCDM method called integrated AHP-CFDM that considers multiple criteria and aims for improving HO rates, APA, and complexity.	✓	✓	✓	✓	✓	✓	LiFi/ WiFi	A & S	✓	✓	✓	✓	✓
Terms			A: analytical/mathematical; S: Simulation; NA: Not specified; CXY: Complexity; MOB: Mobility;												

was considered. The execution time in [39] was used as a complexity metric over a range of user counts.

In [39], unique iterative methods were proposed to address optimization issues with a runtime of 1-10 ms and reduced computing power. Optimization challenges can be solved by reducing packet loss ratio and/or latency and designing/operating low-complexity iterative algorithms.

As shown by [40], ILB's computational difficulty exponentially grows with the number of APs, but MALB-ST and MALB-MT can greatly lower computational complexity over ILB, especially for many LiFi APs. Meanwhile, MALB-MT requires the most HHOs. Since MALB-ST limits some users to WiFi, it produces fewer HHOs than MALB-MT.

Our literature review showed that the research in Table 2 examined lowering complexity, but none considered APA and/or HO decision-making criteria. The only two studies that evaluated, weighted, or prioritized criteria did not include system or technique complexity. However, as those two studies [14], [30] are most relevant to our research, we shall compare their complexity and HO rates. Furthermore, in most HO skipping existing methods, only the user mobility or signal strength is used for skipping the AP.

III. METHODOLOGY

A. SYSTEM SETUP AND CHANNEL MODELLING

The proposed technique in this research consists of two parts, the AHP and the proposed CFDM algorithm, where the AHP is used only for finding the importance of criteria and the proper sortation that will be used by the CFDM algorithm, which will perform all other operations. Using the AHP for finding the weights and level of importance of criteria before using them further can highly provide a high level of reliability when utilizing, measuring, and processing the criteria by another method/algorithm.

Designing a new communication system requires channel modeling. Understanding the channel is essential for effective communication and optimizing, evaluating, and comparing system design approaches. In interior contexts, a LiFi channel model provides channel responses and connection parameters and shows how the channel affects signal quality. Electro-optical parameters of the optical frontends, transmitter and receiver placements, and geometrical and optical qualities of walls and other room objects affect the LiFi channel model.

The user parameters, such as network settings, size of the room, can have different values. However, all the parameters in this study are inspired by previous works and specifically the benchmark works [14], [30].

An indoor LiFi/WiFi hybrid network with many APs is used for the downlink. We assume 16 LiFi APs and 4 WiFi APs. Mobile receivers vary the CSI of integrated LiFi and WiFi lines, requiring regular resource allocation. Detailed system, channel, protocol, and equation models have been defined. Number of LiFi and WiFi access points denoted as N_v and N_r. Each LiFi AP has a multi-LED light. All transportable photon detectors (PD) are ground-facing (irradiation angle equals incidence angle).

Figure 2 depicts an interior service area and user mobility scenario. This project uses MATLAB on a Lenovo laptop with the specs in Table 3.

TABLE 2. Limitations of related works in terms of complexity problem/solution.

Ref.	Complexity-related findings	Complexity		
		Cause of increase	Estimation	Challenges
[19]	None.	Limited variables, user mobility, light-path blockage.	Medium	The reachable APs are limited to the LiFi AP with the highest SINR and the WiFi AP to simplify the process.
[28]	User throughput vs complexity (FLOPS).	multiple variables and user. FL phases.	Med-high	Searching all user-AP connections yields the best solution. Additionally, the proposed approach must conduct SSS or LB in its second step, adding to its complexity.
[29]	None.	multiple variables and user mobility. FL phases.	Low-Medium	In each stage, the CU assigns each user the best AP. The user-allocable APs only include the RF and LiFi AP with the highest SINR to simplify things.
[30]	Normalized throughput vs normalized computational complexity	multiple variables, user mobility and light-path blockage. FL phases.	Low-Medium	The computational complexity was reduced using the FL method.
[31]	None.	Limited variables, and increased FL rules.	Low-Medium	With the learning power of ANN, restricted fuzzy rules were developed, which it may learn from and generalize to make HO decisions. The proposed model improves user QoS and data rate by 40%. This approach is computationally complex as fuzzy inputs increase, affecting system performance.
[35]	None.	There are three nested for-loops in Algorithm 1. The outer loop repeats for all possible C_n combinations. The middle and inner loops repeat A_n and P_n times, respectively.	Med-high	Big O notation has exponential algorithmic complexity, O ($2^{A_n} \times A_n \times P_n$). Exponential algorithms rarely scale. Since a single node has a limited number of APs, scalability would not be an issue for 10 APs.
[37]	Computational complexity vs number of users	Data training and testing phases, user mobility,	Medium	The exhaustive search-based user association trades complexity for upper bound efficiency.
[38]	Computational complexity vs number of users	RL (machine learning approach), training and phases.	Med-high	The DK concept has been used to simplify RL algorithm. Training performance of RL algorithm for three reward functions with and without knowledge transfer. Since exhaustive search and RSS do not train, RL-LA's training difficulty cannot be compared.
[39]	Complexity (Runtime) vs the number of users	Blockages, multiple variables, 3 sequential algorithms.	Med-high	The nature of the iterative method makes theoretically analyzing its optimality and complexity challenging.
[40]	None.	Blockages, mobility, the device's orientation, dataset training, and testing.	Low-Medium	Since polynomial feature mapping is computationally expensive, the Gaussian kernel was used as the second feature mapping approach.
[41]	System throughput vs complexity (FLOPS).	User mobility, blockages,	Low-Medium	For MALB-ST and MALB-MT, computing complexity is essentially irrelevant to network scale.
[42]	None.	Blockages, orientation of LiFi receivers, multiple variables & parameters, three fairness schedulers.	Med-high	Due to iterative computing, the EGT algorithm is more sophisticated than the threshold-based access algorithm (TAA) and the random-access algorithm (RAA). EGT is commonly spread to reduce computational complexity. All users must coordinate with a distributed EGT algorithm. Each user must submit their strategy selections to the APs until the algorithm converges, which uses communication resources.
[43]	None.	Many variables and calculations within 3 separated algorithms.	Med-high	Decisions are simple in the suggested algorithm. Each LED lamp's choice probability distribution must be changed in each 'exponential weights for exploration and exploitation' (EXP3) decision cycle. In the suggested "exponentially-weighted algorithm with linear programming" (ELP), calculating an auxiliary variable related to network architecture and lamp connection is the most difficult stage. However, tracking time-variant system states may become too complicated.

Users in this network are randomly distributed across the service region. Because LiFi APs reuse bandwidth, the system may offer outstanding spatial-spectral efficiency. When light rays are blocked, mobile users' optical CSI changes within the service zone, and optical channel gain may be inadequate. WiFi is installed to increase customer data rates.

The old strategy assigns customers with high optical channel gains to LiFi APs to take advantage of LiFi's great spatial spectrum efficiency, while WiFi APs serve users with low optical CSI. However, our system assigns users using the proposed technique to prevent superfluous HOs.

The CSI of integrated LiFi and WiFi communication lines fluctuates due to receiver mobility, requiring periodic resource allocation at precise intervals. User CSI changes slowly in this investigation, suggesting it persists briefly. System operation can be divided into numerous states in a short time. The idea is that a central unit (CU) monitors the system at frame rates equivalent to the layer's frame rate.

The period T_p is when all users receive allocation results from the CU and AP signals at constant data rates. State pattern number is n. A HO occurs during user mobility when two APs in nearby states serve a user, based on the suggested

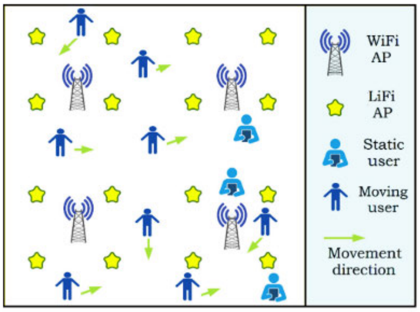


FIGURE 2. System model and scenario.

TABLE 3. Hardware specifications of the device used for the simulation.

Hardware	Specification
CPU	Intel® Core™, Lenovo, China, i5-7200 U CPU @ 2.50 GHz 2.70 GHz
RAM	8.00 GB DDR3
Storage	HDD, 1 TB SSD Lenovo
Operating System	Microsoft Windows 10., 64-bit, x64-based processor

algorithm. The suggested method assigns users based on multi-criteria decisions, while the traditional method of APA and/or LB [49] assigns users with a LiFi data rate above a threshold to LiFi APs and others to WiFi APs. The average user data rate is not included in this study. This study aims to make multicriteria based decisions and examine how each criterion affects the decision and HO rates.

Here N_u is the number of the users; N_s is the number of the working states; $C\mathscr{L} = \{v \mid v \in [1, N_v], v \in Z\}$ is denoted as the set of optical attocells; and $C\mathrm{R} = \{r \mid r \in [1, N_r], r \in Z\}$ is denoted as the set of WiFi cells. The optical channel gain of a LiFi LOS channel is defined as follows:

$$Cg_o = \begin{cases} \dfrac{((L_i+1)\,S_{pd})}{2\pi[(H_d)^2+h^2}g(\theta)\,G_{of}(\theta)\,cos^{L_i}(\phi)\cos(\theta), & \theta < \Theta_R, \\ 0, & \theta > \Theta_R, \end{cases} \tag{1}$$

where L_i is the Lambertian index, that is a parameter of the half-intensity emission angle $\theta_{1/2}$, given as $L_i = -1/\log_2(\cos(\theta\ 1/2))$; S_{pd} is the receiver's physical area of the photo-diode, H_d is the horizontal distance from a LiFi AP to the optical receiver, h is the height of the room, $G_{of}(\theta)$ is the gain of the optical filter, θ is the angle of incidence, ϕ is the angle of irradiance, Θ_R is the half angle of the receiver's FOV, and $Cg(\theta)$ is the concentrator gain:

$$Cg(\theta) = \begin{cases} \dfrac{x^2}{sin^2\Theta_R}, & 0 \le \theta < \Theta_R \\ 0, & \theta > \Theta_R, \end{cases} \tag{2}$$

where x is the refractive index. The LED bulbs in a LiFi system operate in the linear area, where the output optical energy is proportionate to the input voltage. In addition, IM/DD are utilized to ensure that only correct real-valued signals are sent to receivers. Before LiFi transmission, a DC bias voltage source DC is applied to the modulated electric signals. The next formula governs the conversion of the median electric energy of signals to average optical energy:

$$\iota = P_{opt} \Big/ \sqrt{P_t} \tag{3}$$

wherein P_{opt} is the median broadcast optical power of the LiFi AP α, which is proportional to the DC bias voltage source x_{DC}, and P_t is the signal's electric power. The SINR for a given user μ linked to a LiFi AP is expressed as:

$$SINR_{\mu,\alpha} = \frac{(f_{oe}P_{opt}Cg_{\mu,\alpha})^2}{\iota^2 N_{ps}B + \sum (f_{oe}P_{opt}Cg_{\mu,else})^2}, \tag{4}$$

where f_{oe} denotes the efficiency of optical to electric conversion at the receivers; The noise power spectral density is N_{ps} [A^2/Hz], B is the bandwidth, $Cg_{\mu,\alpha}$ is the channel gain between user μ and LiFi AP, and $Cg_{\mu,else}$ is the channel gain between user μ and the interfering LiFi AP. After modulation, at minimum half of the sub-carriers should be employed to recognize the Hermitian conjugate of the complex-valued sign. As a result, only half of the available bandwidth can be used for signal delivery in state n. The Shannon capacity is applied to calculate the attainable data rate between both the user μ and the LiFi AP α, which is stated as:

$$R^{(n)}_{\mu,\alpha} = \frac{B_{ost}}{2} log_2(1 + SINR^{(n)}_{\mu,\alpha}), \tag{5}$$

where B_{ost} is the bandwidth for optical signal transmission. The time division multi-access (TDMA) approach is used in this work, and a proportional decent scheduler is studied. Each WiFi AP in the RF cell has an omnidirectional broadcast station. In the RF system, orthogonal frequency division multiplexing access (OFDMA) is being used. The harmonic responsiveness of the channel is considered to be flattened due to low energy from mirrored routes so that all sub-carriers assigned to a particular user use the same CSI. The WiFi channel gain across users and WiFi APs is estimated as follows:

$$W_{cg} = \sqrt{10\frac{-Lf(d)}{10}}\left(\sqrt{\frac{K}{1+K}}Lf_c + \sqrt{\frac{1}{1+K}}Df_c\right), \tag{6}$$

where $K = 10$ dB is the Rician component for indoor 60GHz connections; $Lf_c = \sqrt{1/2}(1+j)$ is the straight lane fading channel; $Df_c \sim \mathcal{CN}(0,1)$ is the distributed path fading channel; $Lf(d)$ is the equivalent large-scale fading loss in decibels at the isolation range d, given as:

$$Lf(d) = L(d_0 + 10R_e \log_{10}(d/d_0) + Sh_f, \tag{7}$$

wherein $L(d0) = 68$ dB is the benchmark path loss at $d0 = 1$ m; $R_e = 1.6$ is the route loss exponent; and Sh_f is the shadowing factor, which is considered to be a zero mean Gaussian distributed arbitrary variable with a standard deviation of 1.8 dB. The shadowing impact caused by human bodies near the mmWave radio connections is ignored. Each sub-carrier is believed to have equal power, and every user can be flexibly assigned sub-carriers for broadcast. In state n, the data rate obtained by the WiFi link across the user μ and the WiFi AP α can be expressed as:

$$\Upsilon_{\mu,\alpha}^{(n)} = B_{\mu} log_2 \left(1 + \frac{\left[W_{cg_{\mu,\alpha}}^{(n)} \right]^2 P_R}{N_{ps} B_R} \right) \tag{8}$$

wherein B_{μ} is the bandwidth given to the subscriber μ in the WiFi system; and $W_{cg_{\mu,\alpha}}^{(n)}$ is the WiFi channel gain across the user μ and the AP α according to (6). P_R is the power consumption constraint for WiFi APs, and B_R is the WiFi bandwidth. $\Lambda\mu$ is described as the proportion of bandwidth obtained by the user μ. As a result, B_{μ} can be written as:

$$B_{\mu} = \Lambda_{\mu} B_R. \tag{9}$$

B. THE PROPOSED METHOD

This section describes the suggested technique's development procedure. The room's geographic center WiFi AP covers all four corners. Each LiFi AP is integrated within a ceiling LED light fixture and has limited coverage. TDMA allows one AP to serve numerous users, whereas each user can only be allocated to one AP [30]. RWP is assumed for mobile users [49].

User paths should be straight between randomly provided waypoints. User velocity is a uniformly distributed random variable from 0 to maximum. All users' PDs face upward and can only link to one AP. ON-OFF shadowing model is used. Shadowing degree and impacts have not been considered, although future research could investigate them. The LiFi channel SINR is considered to be 0 when the optical channel is blocked for simplicity.

First, the AHP determines criterion weights and relevance in the suggested method. Second, the suggested CFDM algorithm and AHP weights are tested. AHPs need to express the goal and identify options. Since there are usually many decision-making criteria, the AHP next creates a hierarchy with the most generic at the top.

Next, the AHP determines the weight of each criterion in proportion to its connected criteria. Finally, using the lowest criteria, the AHP compares each choice to all others.

The ranking of solutions that meet the given goal will depend on each criterion's significance. The AHP methodology defines the problem and develops a solution. Note that the AHP method is adopted for our work, while the CFDM method is the novel part and the proposed work in this paper.

The integrated AHP-CFDM content is presented in Figure 3. We introduce and examine both phases.

1) PHASE 1: PRE-PROCESSING

This portion includes problem identification of the APA and HO, criteria identification, alternative identification, and other procedures, as indicated in Figure 4. As the decision matrix is created, the criteria are assessed and valued. All criteria are weighted and prioritized. All pre-processing stages are part of AHP.

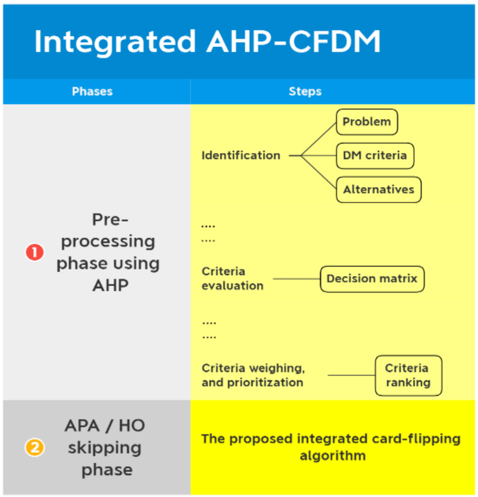


FIGURE 3. Illustration of components of the proposed integrated AHP-CFDM.

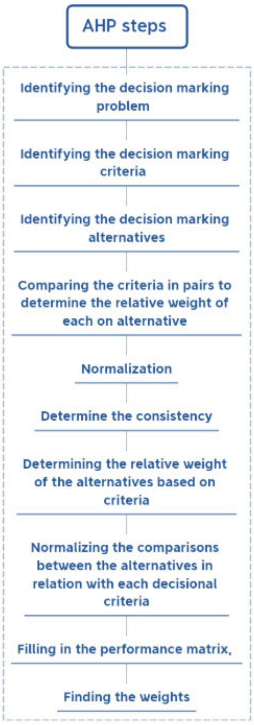


FIGURE 4. AHP steps.

a: IDENTIFICATION STEPS

i) PROBLEM IDENTIFICATION

This section defines the problem to determine what needs fixing. The suggested approach will identify "LiFi" or "WiFi" network access. Specific networks exclusively allow those two groups. If needed, these subscribers are migrated to a

VHO or HHO in the same network. The next section creates a centralized optimization problem using categories. These classifications raise centralized optimization problems. The APA/HO dilemma is complicated by both: the service zones of the two networks may overlap, and WiFi APs have a lower coverage area but a larger system capacity than LiFi APs.

This study completes the AHP pairwise comparison criterion weight and value hierarchies. The proposed strategy prevents needless HOs and ping-pong (PP) effects. User HOs to other APs are redundant if their time-of-stay in a small cell is less than the threshold [46]. PP impact occurs when a user's call is returned to the original cell inside the key period after the neighboring cell's HO decision. The PP rate is the number of PP HOs divided by all HOs (including successful ones), failed HOs, and total HOs.

With the recent advancements in multicriteria and MCDM problem solving and FL methodologies [51], [52], [53], the number of inputs and criteria has expanded, making modern methods/techniques more complex than old ones. This research focuses on complexity and HO.

ii) IDENTIFYING THE DECISION-MAKING CRITERIA

The evaluation criteria needed to identify alternatives are identified and described in this step. Data should be expressed as $C = [Cj]$, where j = 1 and C_N is the number of criteria. This study employed five criteria: LiFi capacity, WiFi capacity, LiFi CDT, occurrence rate, and occupation rate. These exact criteria were utilized in investigations [14], [30], as both are considered benchmark works for comparison to our study.

The most important aspects that could influence mobile users' AP choice are LOS obstructions, blockage rates, mobility, and capacity (data rates), which make the system more realistic. In addition to that, other criteria and settings can be used for different findings. Since our method is new, all criteria that were used in the benchmark works, the FL [30], and the MCDM study [14] will be used in this study for a fair comparison of findings.

After identifying and discussing criteria, the decision matrix is created. To do this, each criterion needs values. Understanding values' origins and justification is vital. This is because certain characteristics have been established in prior studies and others have never been valued. Simulation or literature model analysis will be used to calculate and measure this issue. The criteria are defined and examined as follows:

a. LiFi Capacity and WiFi Capacity: During intercell HOs, the MT's signal strength from the current base station (BS) should affect channel quality. Due to growing data growth, high-capacity communication systems are in demand. This means RF-based wireless communication will face a spectrum shortage [54]. In comparison, the optical domain has a large, unlicensed bandwidth, electromagnetic interference immunity, and privacy safeguards. An effective backbone network is needed to distribute connection capacity amongst LiFi access points spread throughout the interior utilizing OFDM [55].

Many factors affect WiFi and LiFi network capacity for users. The infrared and visible light spectrums are 2600 times the radio frequency spectra of 300 GHz, which determines the network's capacity [56]. The RF spectrum spans 0 to 3×10^{10}, but in the LiFi spectrum, the visible light (VL) is 2600 times larger, spanning from 4 to 7.9×10^{14}.

Throughput and data transmission rates were also identified as important capacity factors [57], [58]. Modulation and data transmission methods also affect network capacity [55], [56], [59]. Increased APs affect system capacity, but cell size (coverage area) does not [60].

Integration with other networks like 5G, which includes new tiers like small cells (SCs), also considers user data usage [57]. Downlink capacity decreases with distance and peak/average power restrictions [61]. Other factors could include physical layer configuration [5], network infrastructure [55], [62], hardware and software design [63], and others.

Considering more electromagnetic spectrum space and applying a number of unique internetworking technologies could increase data throughput. The network's spectral efficiency and capacity will rise when users on the identical frequency reuse the frequency as much as possible [64]. Keeping physical layer settings, the same increases hybrid network capacity and reliability [5].

The need for microscopic cells does not affect system capacity, according to [60], Cell size reduction is crucial to optimizing current cellular communications system performance. The same study found that hybrid LiFi/WiFi systems improve capacity, resilience, security, and dependability. This supports the idea that LiFi, as a supplemental wireless networking strategy, can increase free and enormous wireless capacity and spectrum efficiency in existing RF networks.

Up to saturation, bias current increases LED modulation bandwidth [65], [66]. LEDs act nonlinearly. Thus, driving current and optical power output are nonlinear. A LiFi network's optimal DC bias was found in [67], which maximizes throughput by widening modulation bandwidth. A LED's modulation bandwidth appears to increase from its linear middle to its DC bias.

The authors then examined how these affect SNR and presented two approaches for choosing the ideal DC bias point to maximize connection capacity. Experiments show that raising the bias current from the linear region's midway of 20 mA to the ideal bias current of 30 mA can increase transmission rates by 36%. The methods can be applied independently to user-end devices using the same approach.

The WiFi AP's capacity and the user's capacity can be calculated using WiFi Shannon capacity, WiFi channel SINR, bandwidth, the WiFi AP's transmitted power, WiFi channel gain, and the receiver's power spectral density (PSD) of noise [47].

When calculating LiFi capacity, the electrical SINR for non-negative signals, bandwidth, connection SINR, PSD, detector responsivity, average modulated optical power, and channel gain can be considered [47]. According to [30], the average capacity that the AP can provide to the user was formulated based on the Shannon capacity [68], as follows:

$$r_{i,u}^{(t)} = \begin{Bmatrix} \frac{B_i}{2}\log_2\left(1+\frac{e}{2\pi}\gamma_{i,u}^{(t)}\right), & \text{for LiFi} \\ B_i\log_2\left(1+\gamma_{i,u}^{(t)}\right), & \text{for WiFi} \end{Bmatrix} \tag{10}$$

where $r_{i,u}^{(t)}$ is the capacity that AP i can provide to user u, B_i is the system bandwidth of AP i, and $\gamma_{i,u}^{(t)}$ denotes the received SNR regarding the link between AP i and user u at time point t. Note that the equation (10) is very similar to equation (5), wherein it is formulated for the calculation of the attainable data rate for LiFi users.

Because a network's capacity is distributed among its APs, users, data rate needs, and data consumption, a choice based purely on an AP's capacity may be altered by the number of APs used and users connected. When a hybrid system has varying numbers of APs, as is usually the case, taking a single AP's capacity results in LiFi and WiFi network capacities being unequal.

b. LiFi CDT: The CDT is the average time a mobile device spends at an AP before a HO. A user's CDT may alter depending on pace and direction. CDT, also known as HO dwell time, is "the time the mobile terminal can spend interacting with the cell it is departing (the current cell) until the channel quality reaches a minimal threshold" [69]. Under very general assumptions, the CDT is Gaussian distributed for high HO residual margin M_{ho}. With low Mho, CDT levels are likely to be low.

The LiFi CDT value is critical for this hybrid LiFi system, that is challenged by mobility. The two main VHO systems, immediate vertical handover (I-VHO) and dwell vertical handover (D-VHO), addressed various vertical HO challenges. Finally, HHO/VHO selection involves decision-making or optimization to consider channel quality, resource availability, and CDT [70]. Switching may benefit the network or a user.

The CDT was considered when establishing the HO strategy. HO cost was calculated using CDT [71]. In [10], light-path blockage has been added to the CDT-based LB problem. Short CDTs make the HO process harder and increase ping-pong effects [20]. In a dynamic setting with fast-moving consumers, CDT is low. The statistically obtained CDT can be used to calculate the HO process's percentage of time [71]. User speed varies in hybrid LiFi networks. The study by [46] evaluated 0.2, 0.5, and 1.4 m/s user velocity.

Based on the ORWP mobility model, another study [72] employed 1, 1.4, and 2 m/s for user speed. Some studies used a specified user speed (such as 1, 2, or 5 m/s), whereas others used a range of movement where the speed/velocity is a random variable equally distributed between 0 and a maximum speed [9], [71].

The VHO decision procedure will be activated whenever an interruption happens in order to pick a dwell time prior to the VHO execution. The MT will resume its interrupted transmission using the LOS optical channel if the LOS optical channel resumes before the dwell timer ends; otherwise, a VHO will be carried out.

c. Occurrence Rate and Occupation Rate: It makes logical to focus on shadows and overlook quick fading. It makes logical to focus on shadows and overlook quick fading. Fast-fading crossing events require short fading intervals; therefore, they can be ignored when determining active call termination criteria. Given the above, user movement and impediments affect the remaining criteria, occupation, and occurrence rates, O_{ccp}, and O_{ccr}. Both criteria explain light-path blockages. The degree of channel obstruction affects channel quality. Once a blockage developed, the blockage degree reached its maximum, and no way could deliver throughput.

It measures the percentage of time consumers experience channel obstruction. If the O_{ccp} of channel blockage is high, the user should always be connected to WiFi [1], [10]. The study [1] found O_{ccp} values of 0.2 and 0.8. There were thought to be light-path blockages every minute when the O_{ccp} was 0.1.

Thus, the O_{ccp} concept refers to a user who is continuously blocked without a connection, whereas the CDT concept refers to a user who is continuously connected. O_{ccp} measures channel obstructions per unit time. Switching to WiFi would cause frequent HOs for users with substantial channel obstruction. However, every user's O_{ccp} is gamma distributed with shape factor 1. For each user with a particular O_{ccp}, channel blockage occurrences are assumed to follow a Poisson point process (PPP), which mimics random events like packet arrival at switches [73].

In [10], system throughput was assessed using O_{ccr} at 10/min. O_{ccr} increases, but throughput decreases, according to their study. When $O_{ccr} = 0$, throughput is highest. When channels are blocked, move low-occurrence but high-occupation users to WiFi. If no user has ever had a channel blocked, O_{ccp} and O_{ccr} will be 0. The higher value of these two criteria will reduce throughput.

iii) IDENTIFYING THE ALTERNATIVES

In this case, the available APs from two different networks are the options. Wireless APs are placed thoughtfully so as to cover the entire area. As the LiFi APs reuse the optical spectrum, they cause minimal interference between mobile devices. LiFi APs and WiFi APs (hereafter "APs") stand in for choices 1, 2, …, etc.

The data should be written in the alternative as Matrix A $= [Ai]$, where i $= 1 \ldots n$, which denotes the number of alternatives [74]. Using a pairwise comparison of the criteria to identify their relative relevance, the AHP can generate the following comparison matrix to help with the decision-making process. At this point, we'll determine how much weight each criterion should be given. C $= [cij]$ and the significance they play in making a choice.

b: EVALUATION STEPS

The decision matrix DM is created and proposed here. Analysis and evaluation are needed before introducing the DM for this investigation. After defining and analyzing all the criteria, this part lists their values. The values of the criteria are presented in [14], as well as the values that are used for the DM.

LiFi CDT assumes each 1s has two interval states, which relate to when the CU takes a choice, refreshes, and updates, and the user may experience a HO in the next state. Thus, the LiFi CDT's lowest value is 0.5 s, representing 1 interval state, and its highest is 10 intervals. WiFi capability (protocol 802.11 n) is 100 Mbps with 2.4 GHz carrier frequency and 20 MHz bandwidth [1].

The most two similar studies that employed the identical criterion [14], [30] found that the LiFi CDT may be set to 447 Mbps for 10 users at 5 m/s. Both O_{ccr} and O_{ccp} will be set to maximum 10 n/s and 1.0 n/s, respectively. The minimum values are 0, thus some users may not suffer blockages per session.

Since network capacity is likewise affected by the number of connected users, WiFi capacity should be inversely related to LiFi capacity. So, when WiFi is low, LiFi will be high, when WiFi is low-med, LiFi is Med-high, etc. This part of building WiFi and LiFi capacity criterion comes from user density.

CDT values affect O_{ccr} and O_{ccp} values, and vice versa. Mobility and obstruction rates also affect those three criteria. If mobility is low, the CDT should be high; if it's medium, the CDT should be medium. When mobility is low, blockage is also tested. The CDT is high when the obstruction is low. When mobility and obstruction are medium, CDT is medium. However, medium mobility lowers CDT when obstruction is higher, and vice versa.

For the values of O_{ccr} and O_{ccp}. The value of the O_{ccp} holds an inverse relationship with the CDT value. However, not all events and intervals are equal, this means it is not necessary that every user that is having a long dwell time in the current state (high O_{ccp}) is going to have high a CDT value in the next state. In addition to that, the blockage rates and values are subject to the size of the object causing the shadowing and blockages [42]. Therefore, the values of O_{ccr} and O_{ccp} are determined by considering the values of mobility, blockage rate, and the CDT value.

The O_{ccp} is low independent of mobility when the obstruction is low and the CDT is high. O_{ccr} is affected by high mobility. DMs are produced after specifying and estimating all criteria values. The hybrid LiFi/WiFi network with rule IDs' DM can be derived from the union of the criterion value estimates and the DM's criteria value estimates.

c: WEIGHTING AND PRIORITIZATION STEPS

To give relative priority to each criterion, we must develop a pairwise comparison matrix based on the decision-makers' subjective judgments of the available pairings. A pairwise comparison questionnaire should be created and submitted to a convenience sample of experts from various regions. Figure 5 shows a sample of the questionnaire form used in this study.

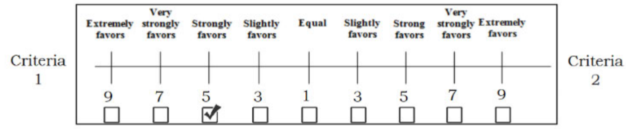


FIGURE 5. Sample of the questionnaire form.

As all criteria and criteria weighing was done by the benchmark work [14], we will follow the study's criteria weighting findings in this step of criteria prioritizing [14]. Thus, questionnaire criteria examination is skipped. However, this section details all criteria weighing processes and formulae. First, verbal judgments like "equally important," "slightly more important," "totally more important," etc., and then giving values on a scale between 1 and 9. Table 4 indicates the importance of one criterion relative to another). Finally, AHP can build this comparison matrix:

$$A = \begin{pmatrix} x_{11} & x_{11} & \dots & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & \dots & x_{2n} \\ \vdots & \vdots & \dots & \dots & \vdots \\ x_{n1} & x_{n2} & \dots & \dots & x_{nn} \end{pmatrix} \text{where, } \begin{cases} x_{ii} = 1 \\ x_{ij} = 1/x_{ij} \end{cases} \tag{11}$$

TABLE 4. Nine scales of pairwise comparisons.

Level of Importance	Description
1	Equal importance
3	Weak importance
5	Essential or strong importance
7	Demonstrated importance
9	Absolute importance
2,4,6,8	Intermediate values between the two adjacent judgments

Back-to-back comparisons of two criteria yield the same significance value [74]. Next, we enter our data into a two-dimensional matrix with n decision criteria for which the table should include the value from comparing two criteria. A new pairwise comparison matrix will contain the ratios from 1/2 to 1/9, with the total of each column representing intensities x, with $x = 1$ to 9 (integer) translated into c using the following relations. We employed a linear scale, $c = x$ [75], [76].

Evaluation of options is done by applying criteria to them and assigning weights accordingly. This comparison results are recorded in a square matrix with "N" components, where "N" is the number of possibilities, similar to criteria evaluation. Matrix count always equals criterion count [74]. Table 5 shows a typical paired comparison matrix.

Using n criteria for evaluation requires $n \times (n-1)/2$ pairwise comparisons. Step 9 assumes that alternatives' relative rankings on each criterion will be weighted. After expert

TABLE 5. Pairwise comparison sample.

	LiFi capacity	WiFi capacity	LiFi CDT	Occurrence rate	Occupation rate
LiFi capacity	W1/ W1	W1/ W2	W1/ W3	W1/ W4	W1/ W5
WiFi capacity	W2/ W1	W2/ W2	W2/ W3	W2/ W4	W2/ W5
LiFi CDT	W3/ W1	W3/ W2	W3/ W3	W3/ W4	W3/ W5
Occurrence rate	W4/ W1	W4/ W2	W4/ W3	W4/ W4	W4/ W5
Occupation rate	W5/ W1	W5/ W2	W5/ W3	W5/ W4	W5/ W5

opinions, a few calculations are needed to calculate criteria weights. Steps include:

1. Normalization for DM

Normalized values are calculated by dividing the comparison value by the total for the corresponding column. Here, we will normalize:

$$a_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} xij} \tag{12}$$

with the normalized value "a_{ij}" being the result of a division by the sum of all the numbers in each column. Afterwards, the weights are computed by averaging the normalized values across rows and then used for the pairwise comparison between criteria; this involves converting the pairwise criterion into weights, where the normalized value was used, and the following condition holds true for the importance coefficients (the weight of decision criteria), which is done using the following equation:

$$A_{norm} \begin{pmatrix} a_{11} & a_{11} & \cdots & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & \cdots & a_{2n} \\ \vdots & \vdots & \cdots & \cdots & \vdots \\ a_{n1} & a_{n2} & \cdots . & \cdots & a_{nn} \end{pmatrix} \tag{13}$$

2. Calculation of All Priority Values (Eigenvector)

In order to assign relative importance to each criterion, the AHP pairwise comparison employs a series of mathematical calculations. After receiving the results from the pair-wise comparisons, a reciprocal matrix is generated. The following formula can be used to get the weights of choice factor i:

$$w_i = \frac{\sum_{j=1}^{n} aij}{n} \quad \text{and} \quad \sum_{j=1}^{n} w_i = 1, \tag{14}$$

where n is the total number of objects being compared. The AHP evaluation should be structured so that the weights are obtained according to the evaluator's personal preferences.

3. Calculation of CR

This is the step when we check for uniformity. Stepping through the steps below will allow us to determine the consistency factor of the selection criteria matrix. According to the AHP definition of consistency, which is defined as "cardinal transitivity between judgements", there should be no inconsistencies in the system. When using Equation (B.4) as a foundation, the first step is to determine the vector priority λmax, which is the product of the matrices of relative weight decision criteria and average weight decision criteria, where $(c.\ k)$ represents the elements of the matrix–vector, which are the product of the "c" matrix and the "k" vector. The following are the steps involved in the AHP method:

$$\lambda max = \sum_{j=1}^{N} \frac{(c.j)}{N.kj} \tag{15}$$

The next step is to calculate a standard deviation of the stochastic uniformity coefficient. The rank of the analyzed matrix, denoted by the letter "N", determines the average stochastic uniformity coefficient, denoted by the letter "R":

$$CI = \frac{\lambda max - N}{N - 1} \tag{16}$$

Finding the uniformity coefficient is the third step. When using formula (16), we get the following results for the "CI" uniformity coefficient: A fourth step is to calculate the matrices' consistency factors. If the consistency relation (CR) is less than 0.10, then the matrix is consistent, and the weight vector may be computed with high confidence:

$$CR = \frac{CI}{RI} \tag{17}$$

In this study, we will use the Alonson/Lamata linear fit, resulting in the CR:

$$CR = \frac{\lambda_{max} - N}{2.7699N - 4.3512 - N} \tag{18}$$

4. Calculation of Row Geometric Mean Method (RGMM)

One of the most common techniques in AHP and MCDM studies was used to assign relative importance to each criterion. Multiples of the weights of criteria and subcriteria (if needed) at the same hierarchical level were applied to the priority weights of criteria. Priorities p_i are calculated using the RGMM. With the pairwise NxN comparison matrix A $= a_{ij}$, we calculate:

$$r_i = exp\left[\frac{1}{N}\sum_{j=1}^{N} 1n\left(a_{ij}\right)\right] = \left(\prod_{i=1}^{N} a_{ij}\right)^{1/N} \tag{19}$$

and normalize:

$$p_i = r_{i./}\sum_{i=1}^{N} r_i \tag{20}$$

5. Weighted Geometric Mean Method (WGMM), and

Aggregation is performed here by using the weighted geometric mean method (WGMM), as follows:

$$Z_i = \prod_{k=1}^{m} Z_{ik}^{w_k}, \quad i = 1, 2, \ldots, n \tag{21}$$

6. AHP Consensus Indicator (AHP-S*).

The aim of the AHP group consensus indicator proposed in is to provide a numerical measure of the group's ability to reach a unified opinion on an issue, or more specifically, to provide an estimate of the degree to which group members will prioritize different outcomes. This metric can take on values between 0 and 100. In this context, 0% represents no consensus at all and 100% represents total agreement. This metric is based on Shannon entropy, specifically the alpha and beta entropies, which are used to describe diversity.

It is a way to assess how much participants in a group share similar priorities, or how much their priorities overlap with one another. When all inputs are run through the RGMM, the combined Shannon alpha and beta entropies are used to determine the AHP consensus. The indicator for consensus can be anywhere from 0% (total disagreement among decision-makers) to 100% (complete consensus between decision makers). N criteria, K participants/decision-makers. Interpretation of the AHP consensus indicator AHP-S$*$:

$$\mathrm{AHP}-\mathrm{S}* = [M - exp(H_{\alpha min})/exp(H_{\alpha max}] \\ /\left[M - exp\left(H_{\alpha min}\right)/exp\left(H_{\lambda max}\right)\right] \quad (22)$$

where $\mathrm{M} = 1/\exp\left(H_\beta\right)$ and $H_{\alpha,\beta,\gamma}$ is the α, β, γ Shannon entropy for the priorities of all K decision-maker participants. Then, we calculated the Shannon alpha entropy by the following formula:

$$H_\alpha = \frac{1}{K}\sum\nolimits_{j=1}^{k}\sum\nolimits_{j=1}^{k} -p_{ij}1np_{ij} \quad (23)$$

The Shannon gamma entropy is calculated as:

$$H_{\alpha\gamma} = \sum\nolimits_{j=1}^{k} -\acute{p}_j 1n\acute{p}_j \quad where\ \acute{p}_j = \frac{1}{N}\sum\nolimits_{i=1}^{N} p_{ij} \quad (24)$$

Then, the Shannon beta entropy is calculated as:

$$H_{\beta=}H_{\alpha\gamma} - H_\alpha \quad (25)$$

After all the steps, the AHP method's results are presented. We present and debate experts' criterion judgments (CJs). The CJs are translated into a pairwise comparison matrix (PCM), the RGMM is generated, and the consolidation matrix (CM), the weighted geometric mean of all participants, is calculated. Finally, weight results are shown. Weights show each attribute's relative value according to eight experts. The study [14] weighted data from 10-year LiFi, VLC, and optical communication experts. In Table 6, all experts' weighted preferences for individual criteria are compared to other criteria. Expert judgment results match the study authors' comparative questionnaire.

To comprehend the significance of expert CJs, all criteria data must be transformed to PCM. In Table 7, PCM data will be used to compute the final weights of each criterion for all participants. Table 8 shows RGMM values. Both the aggregate of individual judgments (AIJs) and the aggregate of individual priorities (AIPs) are taken into account in the AHP. The final priority of the options for the two aggregation procedures (AIJs and AIPs) is produced when the RGMM periodization procedure is used. Table 9 shows consolidation matrix values. If the WGMM is used for aggregation and the RGMM for prioritization, the group judgment error is the geometric mean of the weights assigned to the individuals' judgment errors. Table 10 shows all matrices' RGMM priority vectors and GCIs. RGMM periodization will produce an adequate geometric consistency index if the decision makers' judgments are inconsistent. Final AHP weight values include the normalized primary Eigenvector, which calculates each criteria weight as a percentage and sums all criteria weights to 100%.

Priority vectors and individual matrices show acceptable inconsistency (GCI $<$ 0.35), with a GCI of 0.33 in this study. A 9.1% CR is fine as long as it stays below 10%. Saaty recommends including the CR in the conventional AHP to measure individual inconsistency [74]. The Lambda value is 5.410 and the α value is 0.1. The EVM check is 1.2E-09. Effective earned value management requires careful project expenditure control.

However, using this method to assess deadline progress yields considerable disparities. The earned value has been changed multiple times to account for these accuracy gaps while assessing project timeline progress. This tracking works best with earned value management. The measurement of work (scope) at the planned cost and the baseline measurement (scope, schedule, and cost) are called earned value management (EVM) [77]. "LiFi capacity" is weighted highest at 0.5928, followed by "LiFi CDT" at 0.1968. Eigenvalue: 5.40995468. Eigenvalues can be ordered from largest to smallest by absolute value.

Maximal Eigenvalue is the largest absolute Eigenvalue. Complex numbers can be eigenvalues of polynomials. Luckily, pairwise comparison matrices cannot do this, so we can search solely for real values. AHP consensus indication (AHP-S*) is 77.8%, which is high. Calculated using CR value. Pairwise comparison consistency is measured by the CR. AHP consensus indicators help ensure process reliability and validity. The AHP procedure can yield trustworthy and valid findings that accurately reflect the decision-maker's preferences and priorities by ensuring consistent pairwise comparisons. There are many benefits to finding the AHP consensus indicator. Finding the AHP consensus indicator is crucial to guaranteeing the credibility and legitimacy of the AHP process and improving decision-making openness, accountability, and trustworthiness.

2) PHASE 2: APA AND HO SKIPPING: THE PROPOSED CFDM ALGORITHM

This section explains this study's development method. This study proposes a dynamic APA/HO technique to find the best AP assignment and HO skipping to reduce HO rates and complexity.

The proposed CFDM technique is different in nature compared to existing APA and/or HO methods. A few differences can be highlighted as follows:

TABLE 6. CJ results obtained from the experts.

	Q1		Q2		Q3		Q4		Q5		Q6		Q7		Q8		Q9		Q10	
	LiFi capacity	WiFi capacity	LiFi capacity	LiFi CDT	LiFi capacity	Occurrence rate	LiFi capacity	Occupation rate	WiFi capacity	LiFi CDT	WiFi capacity	Occurrence rate	WiFi capacity	Occupation rate	LiFi CDT	Occurrence rate	LiFi CDT	Occupation rate	Occurrence rate	Occupation rate
EXPERT 1	-	5	-	9	7	-	1	1	9	-	5	-	5	-	9	-	7	-	7	-
EXPERT 2	9	-	7	-	7	-	7	-	-	5	5	-	5	-	5	-	7	-	1	1
EXPERT 3	7	-	9	-	5	-	7	-	-	7	5	-	5	-	9	-	7	-	1	1
EXPERT 4	7	-	7	-	7	-	9	-	-	7	-	5	-	5	-	7	9	-	1	1
EXPERT 5	9	-	9	-	7	-	9	-	-	7	7	-	5	-	5	-	9	-	1	1
EXPERT 6	9	-	7	-	9	-	7	-	-	7	7	-	5	-	3	-	9	-	1	1
EXPERT 7	9	-	5	-	7	-	9	-	-	5		-	9	-	7	-	5	-	1	1
EXPERT 8	7	-	5	-	7	-	7	-	-	5	3	-	5	-	9	-	5	-	1	1

TABLE 7. PCM for each expert of all criteria and the CM for all participants.

	8= k Number of Participants 5 = n Number of Criteria										
EXPERT ID	LiFi capacity	WiFi capacity	LiFi CDT	Occurrence rate	Occupation rate	EXPERT ID	LiFi capacity	WiFi capacity	LiFi CDT	Occurrence rate	Occupation rate
Expert 1	1	1/5	9	7	1	Expert 5	1	9	9	7	9
	5	1	9	5	9		1/9	1	1/7	7	5
	1/9	1/9	1	7	9		1/9	7	1	5	9
	1/7	1/5	1/7	1	7		1/7	1/7	1/5	1	1
	1	1/9	1/9	1/7	1		1/9	1/5	1/9	1	1
Expert 2	1	9	7	7	7	Expert 6	1	9	7	9	9
	1/9	1	1/5	5	5		1/9	1	7	1/7	5
	1/7	5	1	5	7		1/7	1/7	1	3	9
	1/7	1/5	1/5	1	1		1/9	7	1/3	1	1
	1/7	1/5	1/7	1	1		1/9	1/5	1/9	1	1
Expert 3	1	7	9	5	7	Expert 7	1	9	5	7	9
	1/7	1	1/7	5	5		1/9	1	1/5	9	5
	1/9	7	1	9	7		1/5	5	1	7	5
	1/5	1/5	1/9	1	1		1/7	1/9	1/7	1	1
	1/7	1/5	1/7	1	1		1/9	1/5	1/5	1	1
Expert 4	1	7	7	7	9	Expert 8	1	7	5	7	7
	1/7	1	1/7	1/5	1/5		1/7	1	1/5	3	5
	1/7	7	1	1/7	9		1/5	5	1	9	5
	1/7	5	7	1	1		1/7	1/3	1/9	1	1
	1/9	5	1/9	1	1		1/7	1/5	1/5	1	1

TABLE 8. RGMM for all the criteria by each expert.

		Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Expert 7	Expert 8
RGMM	LiFi capacity	27.7%	60.6%	58.2%	54.1%	61.6%	52.1%	57.9%	55.4%
	WiFi capacity	46.4%	10.3%	9.2%	2.7%	9.7%	17.6%	12.5%	10.1%
	LiFi CDT	14.5%	21.9%	26.1%	16.7%	22.7%	14.2%	22.7%	26.4%
	Occurrence rate	6.8%	3.8%	3.4%	18.8%	3.3%	12.5%	3.4%	3.9%
	Occupation rate	4.6%	3.5%	3.1%	7.7%	2.7%	3.6%	5.4%	4.1%

1. **Criteria values:** our method divides the criteria into several segments (segmentation), where each range of values in each segment is used for different decision. On the other hand, in previous APA/HO methods, each criterion is treated as one range of values.
2. **Threshold values per criteria:** two different threshold values for each criterion are assigned that separate the decisions. Multiple and different decisions per criteria are performed, compared to only two decisions linked to one or maximum two criteria in previous methods.
3. **Computation:** each criterion is considered UNFLIPPED until it is processed, it will be marked as FLIPPED. This reduces the computations and therefore the complexity. While in previous methods, all criteria are measured and computed at the same time.

TABLE 9. CM of weighted geometric mean of all participants.

		LiFi Capacity	WiFi Capacity	LiFi CDT	Occurrence Rate	Occupation Rate
Consolidated	LiFi capacity		5.089	7.071	6.926	6.223
	WiFi capacity	0.196		0.442	2.258	3.599
	LiFi CDT	0.141	2.26		3.789	7.297
	Occurrence rate	0.144	0.443	0.264		1.275
	Occupation rate	0.161	0.278	0.137	0.784	

TABLE 10. AHP weight results.

Matrix	LiFi capacity	WiFi capacity	LiFi CDT	Occurrence rate	Occupation rate	Normalized Principal Eigenvector 100%	Weights	Values		Criteria ranking
LiFi capacity	1	5	7	7	6 2/9	59.28%	0.5928	Consistency Ratio CR:	9.1%	1st
WiFi capacity	1/5	1	4/9	2 1/4	3 3/5	11.07%	0.1107	GCI:	0.33	3rd
LiFi CDT	1/7	2 1/4	1	3 4/5	7 2/7	19.68%	0.1968	EVM Check	1.2E-09	2nd
Occurrence rate	1/7	4/9	1/4	1	1 2/7	5.52%	0.0552	α	0.1	4th
Occupation rate	1/6	2/7	1/7	7/9	1	4.45%	0.0445	AHP-S*	77.8%	5th
Consistency Ratio (CR), Geometric Consistency Index (GCI), Earned Value Management (EVM), AHP consensus indicator: (AHP-S*), Mean relative Error (MRE), and Lambada (Alonson/Lambada). Note: In this work, we used a linear scale.						SUM =100%	SUM = 1	Lambda	5.410	Criteria ranking is the final sequence used for the DM process by the proposed CFDM
								Eigenvalue	5.40995468	
								Error:	1.0E-08	
								Iterations	7.0E+00	

4. **Criteria grouping:** while the AHP is used for sorting the criteria based on their importance in the process of APA and HO, unsimilar criteria (WiFi network criteria) might take a sequence among the sorted LiFi criteria, which therefore might lead to a HO and transfer the user to a different network. This problem is solved by grouping the criteria by the proposed CFDM based on network type to prefer a network over the other. While previous methods, especially the MCDM and FL methods, sort the criteria without grouping them, which could lead to increased HO rates and unpreferred network assignment.

In this novel approach, multiple values for each criterion are considered simultaneously. For objective comparisons between the proposed technique and the benchmark works, different scenarios are used, with the criterion values varying based on various categories and circumstances. As can be seen in Figure 6, each criterion is broken down into three fragments, the first of which is designated as having a low value, the second as having a medium value, and the third as having a high value.

Let C_n denote the criteria number, SEG_n denotes the segment number, and C_n SEG_n is the segment number of the criteria. For example, $C_1S_1V_1$ refers to the first value of the first segment from first criteria C_1. $C_1S_1V_2$ supposed to be the second segment value, and $C_1S_1V_3$ is the third and final segment value, where three segments are assumed for each criterion in our method. The first value of the segment is the lowest, the second holds the medium range value of the total, and the third segment holds the highest range from the third segment over the total criteria values.

Let C_nT_1 be the first threshold value that resides between SEG_1 and SEG_2 of each criterion, which points at %33.333 at the end of the first segment, and C_nT_2 be the second threshold value that resides between SEG_2 and SEG_3 of each criterion, which points at %66.666 at the end of the second segment. This means every criterion has two threshold values different than other criteria that are divided based on their segments. The segment values of each criterion are combined in order to determine the final value of each criterion, denoted as SEG_{sum}. These threshold values will be used for further decisions. The threshold value is a percentage value taken from the total value of each criterion. This means the values must be pre-determined for all considered criteria when designing any similar technique. The values of the segments are calculated as:

$$SEG_n = \begin{pmatrix} 1, & C_nS_nV_n \leq C_nT_1 \\ 2, & C_nS_nV_n > C_nT_1, C_nS_nV_n \leq C_nT_2 \\ 3, & C_nS_nV_n > C_nT_2, C_nS_nV_n \leq C_{n_{max}} \end{pmatrix} V_n, T_1 \in C_n \tag{26}$$

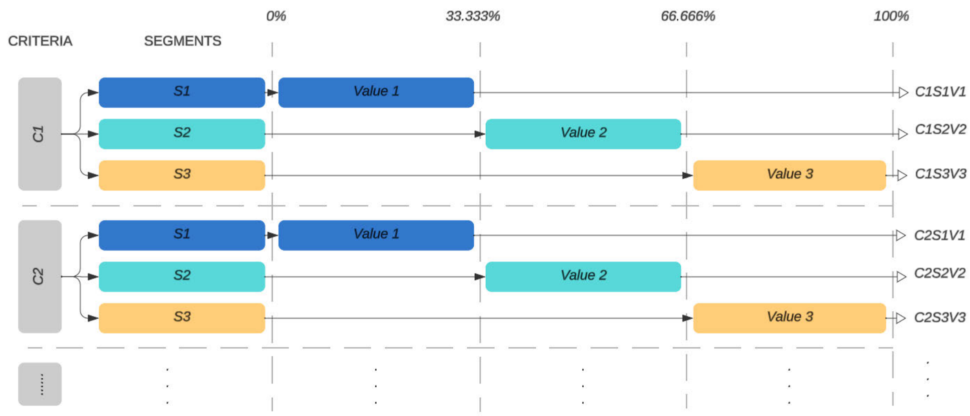


FIGURE 6. Criteria segments and thresholds used in the proposed technique.

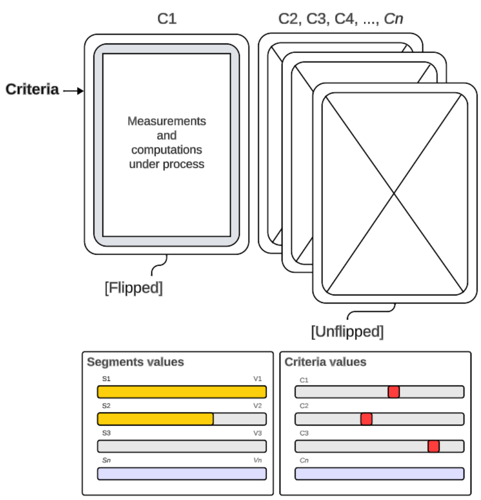


FIGURE 7. Basic principle of the proposed card-flipping technique and flipping principal illustration.

where $C_{n_{max}}$ is the maximum value of the targeted criteria. The total value of the criteria C_nV is the result of summation of all segments as follows:

$$C_nV = SEG_{sum} = SEG_1 + SEG_2 + \ldots + SEG_n. \quad (27)$$

The criteria are treated as **CARDS**, each criterion is one card. In Figure 7, the chosen criteria are **FLIPPED**, where $C_{status} = 1$, and then computed and measured, while the **UNFLIPPED** cards, where $C_{status} = 0$, are on hold before performing any computations and measurements related to them.

The measurements of the **FLIPPED** cards include the segments and threshold values. Furthermore, after attaining the values of the segments, the values of each criterion are obtained for making a decision based on the proposed algorithm. The value of each criterion is given by

$$C_{status} = \begin{pmatrix} 0, & UNFLIPPED \\ 1, & FLIPPED \end{pmatrix} \quad (28)$$

The conditions of making decisions are based on the above calculations. After segments of the first criteria are examined, three decisions are made considering (26), (27), and (28), as follows:

$$DEC = \begin{pmatrix} SKIP, & C_nV \in SEG_1 \\ FLIP, & C_nV \in SEG_2 \\ ASSIGN, & C_nV \in SEG_3 \end{pmatrix} V_n, T_1 \in C_n \quad (29)$$

where the first condition as SKIP, the second condition as FLIP, and the third condition as ASSIGN, all the conditions are explained as follows:

1. **SKIP**: a decision is made where the current AP keeps the connection, and the HO process is skipped. This step is acting like the HO skipping method [20]. This also applies to all skipping steps after the calculations of each criterion whenever the first condition is met. Moreover, whenever any criteria reach the skipping process, the connection of users continues without any HO, and that will reduce the overall HO rates.
2. **FLIP**: a decision is on hold; the second card is FLIPPED for further measurements whenever the second condition is met. This step includes checking and computing the next criteria. The sorting of all criteria is based on the sequence obtained from the AHP technique, which comes from the priority and importance of the criteria. Moreover, in case all cards are FLIPPED except the last one (C max – 1) and no decision is made, the value of the last card will be used for making a decision.
3. **ASSIGN**: a decision is made where the targeted AP is chosen whenever the third condition is met. In this step, a HO occurs every time a high value is obtained for the computed card.

While the initial process of the three conditions is shown in Figure 8, on the other hand, as seen in Figure 7, the basic principle is shown for an infinite number of criteria. Therefore, the final conditions for our proposed technique are derived, when 4 over 5 cards are FLIPPED, the final card is used for making a decision where the final card is divided

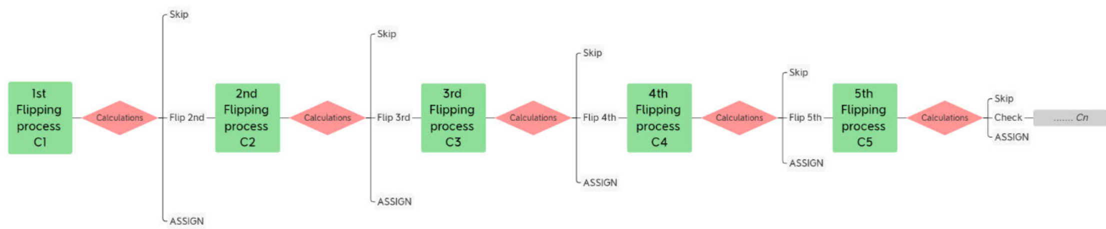


FIGURE 8. Initial conditions for skipping and APA of the CFDM.

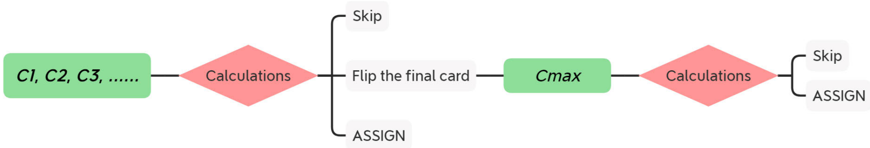


FIGURE 9. Final condition for skipping and APA of the CFDM.

only into two segments, low and high. The final conditions are as shown in Figure 9.

After setting the main build blocks of the proposed technique, it is important to take into account the nature and features of the criteria. Since our proposed method relies on taking measurements of the criteria before making a decision, the low and high values of the criteria cannot be used directly in the algorithm.

The criterion used to determine the placement will be categorized as either benefit criteria (BC) or cost criteria (CC), as seen in [14], in which case the benefit criterion is thought to be the best when it is increased and the worst when it is dropped. When values are minimized, however, they are deemed to be optimal, and the opposite is true when values are increased.

Since the nature of the variables and elements in the system is fixed, for instance, a BC cannot be changed to a CC, and vice versa, the researcher's knowledge of the system is crucial to the determination and identification of each criterion as a BC or CC.

Bear in mind that figuring out how to properly establish each criterion is crucial, for the simple reason that a mistake in identifying the criterion in this case could lead to false-positive ranking values for some or all criteria. The classification of the used criteria is shown in Table 11.

TABLE 11. The BC and CC classification for the given criteria.

Criteria	Benefits Criteria	Cost Criteria
LiFi capacity	✓	
WiFi capacity	✓	
LiFi CDT	✓	
Occupation rate		✓
Occurrence rate		✓

As seen in Figure 8, the initial conditions include SKIPPING the APA when the criteria value is within the first segment (low), while ASSIGNING the targeted AP when the value of the criteria lies within the third segment (high). However, when considering BC and CC, this is not always the case. When the criteria are a BC, the default condition remains the same, while when considering CC, the situation of conditions is reversed, where the SKIP process is performed when the criteria value lies within the third segment and the ASSIGN process when the value lies within the first segment. Where the CC value is reversed over the 100% value of the criteria for normalizing the process and to be understandable. As shown in Figure 10.

Using the traditional MCDM method as in [14], all criteria are combined during the processing and measurements, and then a decision is made based on specific calculations. However, in our proposed method, the criteria must be identified and separated according to the network/AP type.

The proposed method mainly focuses on assigning LiFi first, if the conditions that come from LiFi criteria are met in order to ensure high service delivered to the users, including the data rates, then the alternative network is considered the second choice, which is WiFi in this hybrid network system. After obtaining the sequence of all criteria from AHP, the criteria of LiFi are considered the first group criteria, network is considered the second group criteria. Then the new separation and sorting of the criteria based on the network type is given as groups, and the new formulation of the criteria sequence is shown in Figure 11.

As seen in Figure 11, the sorting of LiFi criteria is shifted after taking the WiFi criteria out of the group, in this way, the decision maker can measure the values of LiFi criteria first to allow the allocation of LiFi AP before considering assigning the WiFi AP.

In addition, separating the WiFi related criteria makes it possible to reflect each network assignment possibility discretely. This means making the WiFi related criteria the final criteria that controls the final decision in case all previous criteria score "Medium". When there is only one criterion

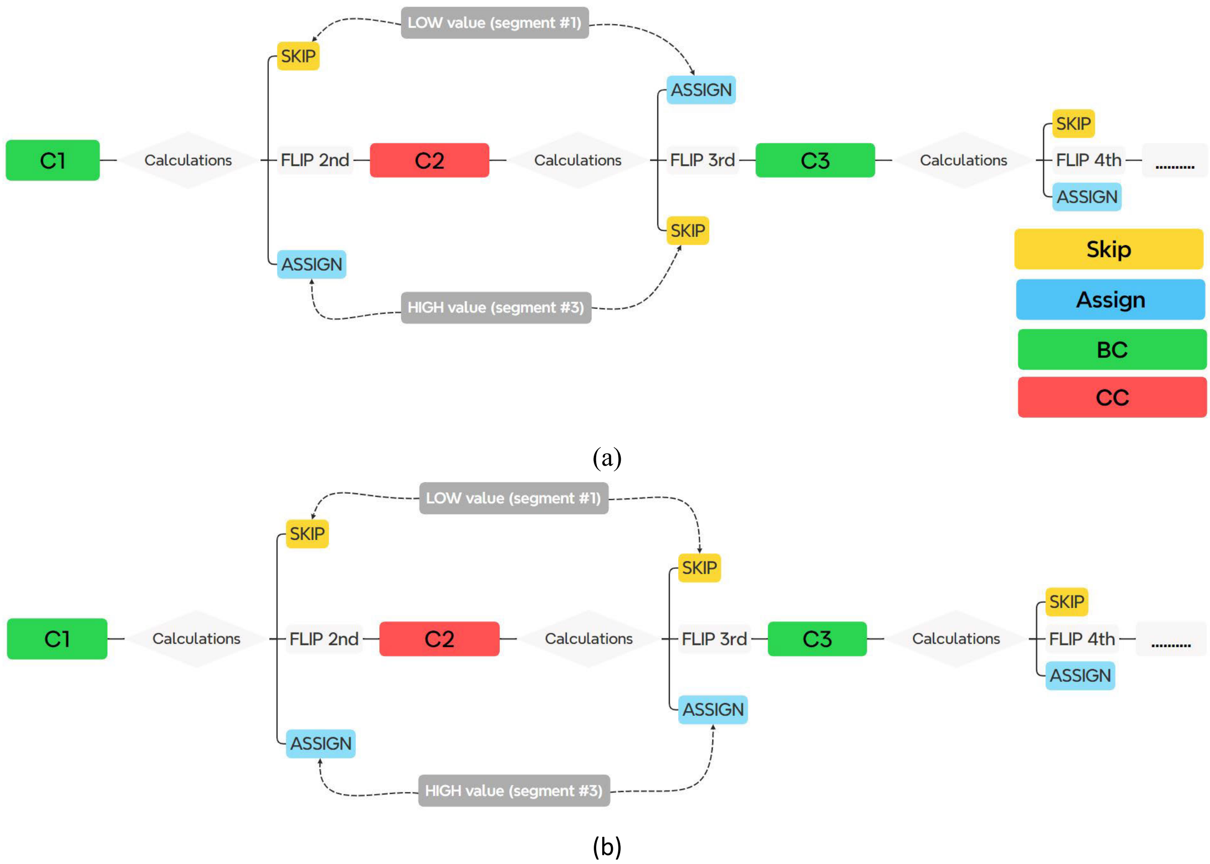


FIGURE 10. SKIP and ASSIGN processes after considering the BC and CC. (a) before reversing the CC values, and (b) after the reverse.

in the second group, that criteria will consist of only two segments that is labeled as "Low" and "High". In case there are two criteria in the second group, the first one will be divided into three segments, like the LiFi criteria, and the last one will be divided to two segments, where one threshold is user that divides the two segments as 50/50, which is denoted as CnT_3. The first group of criteria is denoted as CG_1, and the second group is denoted as CG_2. In addition, the criteria in the first group are denoted as CG_1N and in the second are CG_2N, and the number of the last criteria in the second group is denoted as CG_2L.

The ASSIGN process refers to the process of choosing the WiFi AP or the LiFi AP, but the assignment of an AP varies in each card. For example, the first group of cards consists of LiFi related criteria, and the second group is WiFi related criteria. When the value of a card in the first group scores high, it is supposed to assign the user to the LiFi AP and assign the user to WiFi AP if the card belongs to the second group. However, it is considered the default process, and this rule is applied when the card is BC, but when the card belongs to the CC, the process of AP assignment is reversed.

For example, the third and fourth cards are CC, where occurrence and occupation rates of blockage in the first group of cards (LiFi related criteria) are calculated, and the AP assigned will be WiFi AP. This is because the proposed method aims to avoid assigning the user to the targeted AP if any blockage of the LiFi LOS occurs. Figure 12 shows the assigned APs in both cases. The steps and details of the proposed CFDM algorithm is shown in Figure 13.

The following are some highlights of the procedure preceded by Algorithm 1 including the APA, HO procedure, and the calculations of HO rates, skipping rates, assigning rates, and complexity.

TABLE 12. CFDM simulation parameters.

Parameter	Value	Details
Number of criteria (C_n)	5	The maximum can be set to 5 because the flipping probability reaches its minimum with 5 criteria.
Number of segments (C_n SEG_n)	3	Because the CFDM has 3 decisions per criteria, each segment consists of a range of values where each range triggers a decision.
Number of thresholds (C_nT_1; C_nT_2)	3	This value is related to the number of segments, where each threshold value equals the end of each segment.

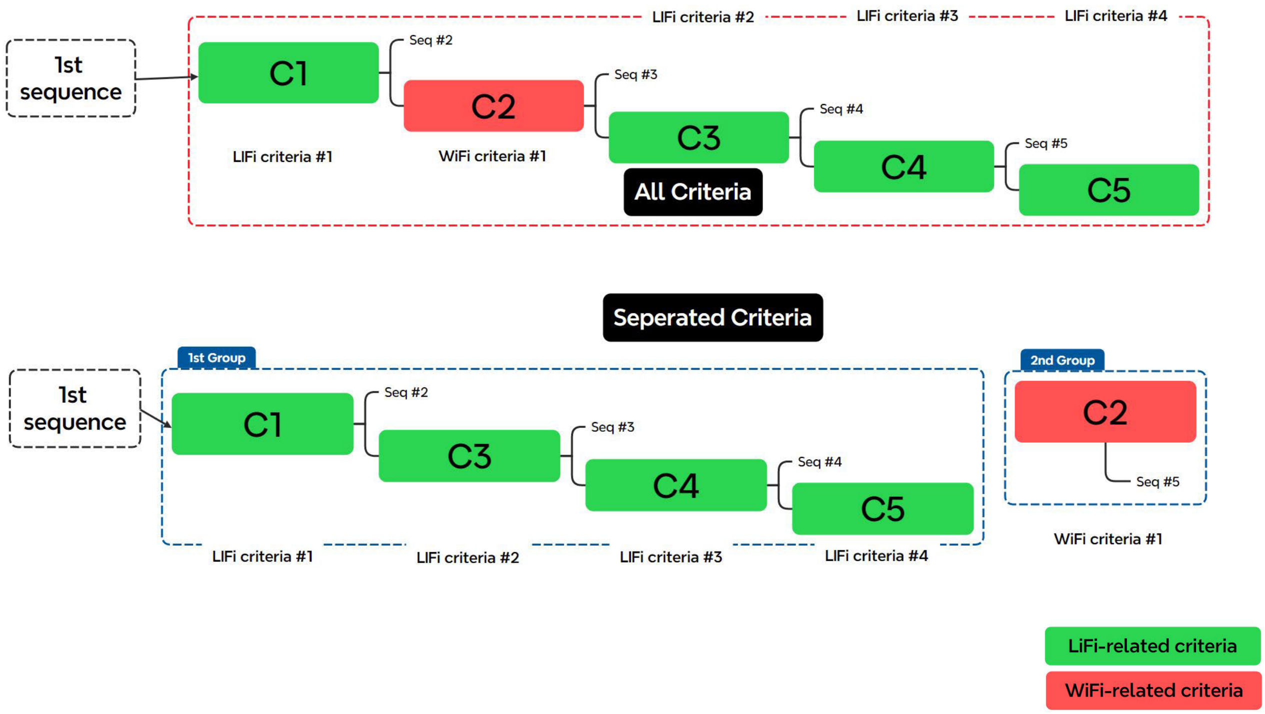


FIGURE 11. Final condition for skipping and APA after criteria sorting, and separation (criteria grouping).

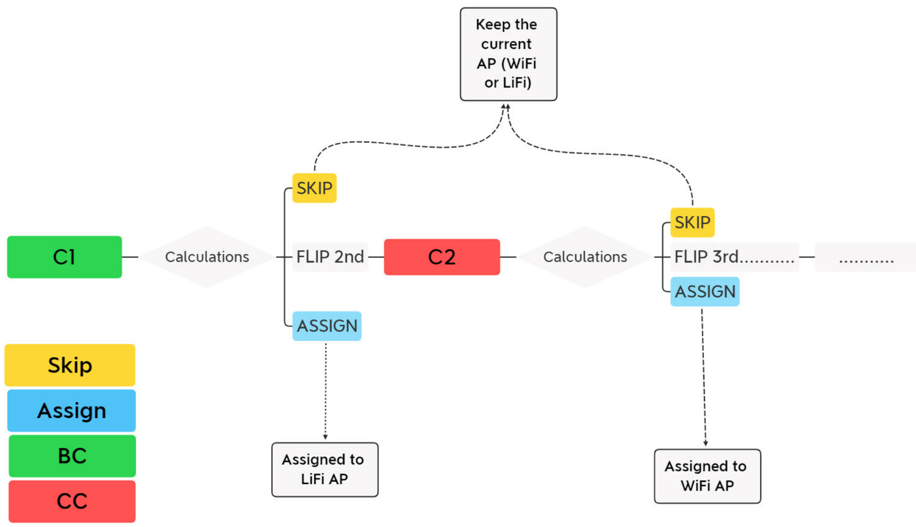


FIGURE 12. Assignment of AP type after considering the CC and BC in the proposed CFDM technique.

- **START**: starting the system and checking all the settings and configurations.
- **INPUT**: variables are set and created, such as N_s, N_u, N_r, N_v. Other parameters are checked that are exclusively related to the CFDM algorithm, such as the criteria (C_n), the number of segments for all criteria (C_nSEG_n), the threshold values including (C_nT_1; C_nT_2) for the first group of criteria CG_1 and the second group CG_2 as well, and the last criteria in the second group CG_2L. The area of the simulation is also identified, as well as the number of LiFi APs and WiFi APs. All the parameters of the CFDM algorithm are shown in Table 12. However, the values presented in the table are standardized but also can vary based on the development of the current version of the proposed CFDM algorithm.
- **PROCESS**: This phase consists of the main functions in the proposed algorithm. The beginning of the process starts as the time of the running simulation is within

The proposed CFDM algorithm	
Start:	denote $\acute{\alpha}_{\mu}$ as the AP allocated to user μ;
Input:	N_s, N_u, N_r, N_v; C_n; $C_n\ SEG_n$; C_nT_1; C_nT_2; C_nT_3; CG_1; CG_2; CG_2L;
Process:	1. While $n \leq N_s$ do 2. Obtain CSI for all connected users and all APs in both systems 3. DIVIDE and SORT all criteria C_n based on AHP results and sorting 4. For all moving users μ do 5. While all cards are UNFLIPPED $\rightarrow C_n = 0$ 6. While $(C_n \leq CG_1N)$ && $(C_n \leq CG_2L-1) \rightarrow C_n \in CG_1, CG_2$ 7. FLIP the next card $C_n = 1$ (card is FLIPPED) 8. Compute and measure the current card values 9. If $(C_nSEG_{sum} \leq C_nT_1)$ 10. SKIP the HO and keep the current AP α connection 11. Else If $(C_nSEG_{sum} > C_nT_2)$ 12. HO and ASSIGN the targeted AP α for the current user μ 13. Else If $(C_nSEG_{sum} > C_nT_1)$ && $(C_nSEG_{sum} \leq C_nT_2)$ 14. FLIP the next card $\rightarrow C_{n+1}$ 15. End If 16. End If 17. End If 18. While $(C_n = CG_2L) \rightarrow C_n \in CG_2$ 19. If $(C_nSEG_{sum} \leq C_nT_3)$ 20. SKIP the HO and keep the current AP α connection 21. Else 22. HO and ASSIGN the targeted AP α for the current user μ 23. End If 24. End While 25. Update AP $\acute{\alpha}_{\mu}$ in the current state 26. End While 27. $n \leftarrow n + 1$ 28. Refresh and update the CSI at the CU; UNFLIP all cards $\rightarrow C_n = 0$ (Cards are UNFLIPPED) 29. Update AP $\acute{\alpha}_{\mu}$ in the current state 30. End While 31. End for 32. Calculate VHO rates; Complexity; Flipping rate; Skipping rate; Assignment rate; Switching probability 33. End While
Output:	VHO rates; Complexity; Flipping rate; Skipping rate; Assignment rate; Switching probability;

FIGURE 13. The proposed CFDM algorithm.

the total time N_s. The CSI of all users is obtained, and all considered criteria are divided and sorted based on the AHP findings and after the consideration of the CC and BC, as well as the criteria separation. Then the process of card-flipping begins for moving users. All criteria, except the last one, are considered then at the time of flipping the cards, where every function involved in the FLIPPED card is measured and calculated for decisions, from line (5) to (32). The process from lines (9) to (17) performs the SKIPPING, ASSIGNING, and FLIPPING procedures based on the segments' values and thresholds. If no decision is made after FLIPPING all criteria and the last criteria is FLIPPED, then the process from line (18) to (25) takes place, otherwise, the execution of these lines will be skipped, and therefore, complexity is reduced for the current cycle.

At the end of each cycle, the information is updated, and all cards are UNFLIPPED, and the system starts over the process in the next cycle n $\leftarrow$ n + 1. After making all decisions related to SKIPPING, ASSIGNING, and FLIPPING throughout all criteria, the system calculated the VHO rates, complexity, flipping rate, skipping rate, assignment rate, and switching probability.

- **OUTPUT**: The output provides the final results needed that draw investigations and findings.

The integration of AHP and the proposed CFDM is important as it presents the basic steps before the execution of the algorithm. The system model and process flow are shown in Figure 14.

IV. RESULTS AND DISCUSSION

Here, we present experimental evidence supporting the validity of the proposed system model and our unique approach. We use MATLAB's included simulation tools to try out several iterations of our CFDM method.

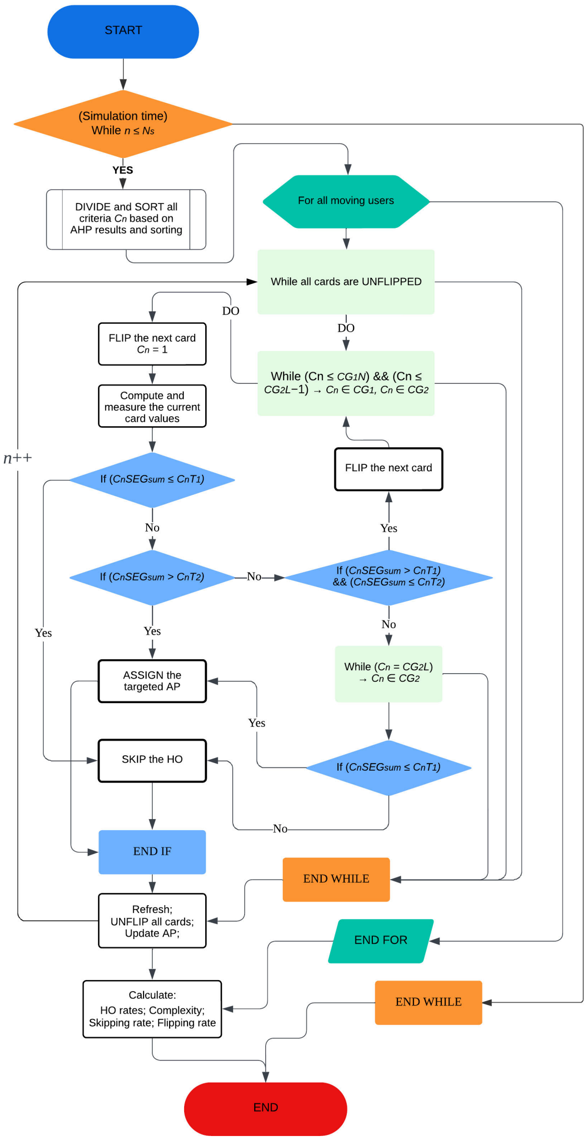


FIGURE 14. System model process flow diagram.

First, the performance metrics and associated measures are described here. The simulation findings are explained afterward.

We will evaluate our proposed system against established methodologies like the FL approach and the MCDM integrated AHP-VIKOR approach to assist and appreciate its full potential. In this scenario, 16 LiFi APs and 4 WiFi APs are used in an evenly spread simulation area. When an automatic HO happens between two APs, we also take into account the possibility of VHO.

Users' speeds range from zero to a few meters per second as they wander around at will. The HO overhead has a Poisson distribution in all directions. A user cannot be redirected to a different AP due to HO overhead, even if they have traversed the HO circle or met a triggering condition like optical gain. Determining an APA through the HO process can take longer than necessary due to a number of issues, such as resource allocation and data rate limitations. Because of the need for a constant data transfer rate in hybrid networks, a low HO rate connection is crucial.

In order to measure the performance of our model, this work's performance evaluation can provide enough details about the achieved results by the proposed technique CFDM and be compared with two benchmark works, the FL method [30] and the MCDM method [14]. The results presented in this section will be divided into two sections, preliminary results, and main results. Simulation results will be presented and discussed in both sections.

A. PRELIMINARY RESULTS

The findings of the suggested method are presented in this part; our approach is the first of its kind to employ the card-flipping idea for AP assignment in hybrid wireless networks; the number of flips per card is demonstrated. Since our suggested system includes a combination of AP skipping, HO, and AP assignment, we also track and compare the frequency with which APs are skipped.

For a comprehensive grasp of the APA facet, the ratio of LiFi assignments to WiFi assignments is also displayed. All of the people move around at random speeds, which can be anything from zero to two meters per second. Both the suggested approach and the other reference works are simulated with 99 iterations. The number of users assumed in the simulation scenario is equal to the number of iterations. In each iteration, a new user is assumed to go through the process of the proposed CFDM technique.

Since users move around, the criteria's value tends to fluctuate at random, and our proposed technique is novel and depends heavily on the criteria's values for AP skipping, APA process, and HO. We run the simulation three times and show three sets of results for each type of result to help readers get a handle on the idea behind the new approach.

Each criterion is dealt out like a card, and the suggested method measures the worth of just one at a time. Each condition in this respect is treated as an UNFLIPPED card in the outset, and once a card has been processed by the system, it is treated as FLIPPED. Figure 15 depicts the total number of FLIPPED cards with their respective counts of measurements displayed. As an example, in the first run, the first card is flipped 99 times; in the second and third runs, the card is flipped and measured in each iteration.

The second card has been flipped 34 times, 31 times, and 33 times throughput the three runs. This is 34%, 31%, and 33% of the first card. As the proposed technique aims to flip the next card only when the value of the current card is within the second segment $SEG_n 2$ that relies between the first and the threshold, C_nT_1 and C_nT_2. The rest of the values with the first and third segments, $SEG_n 1$, $SEG_n 3$, represent other decisions such as the skip, and the HO and assign process. As the first card represents the LiFi capacity, users will be assigned or skipped based on the value of the obtainable

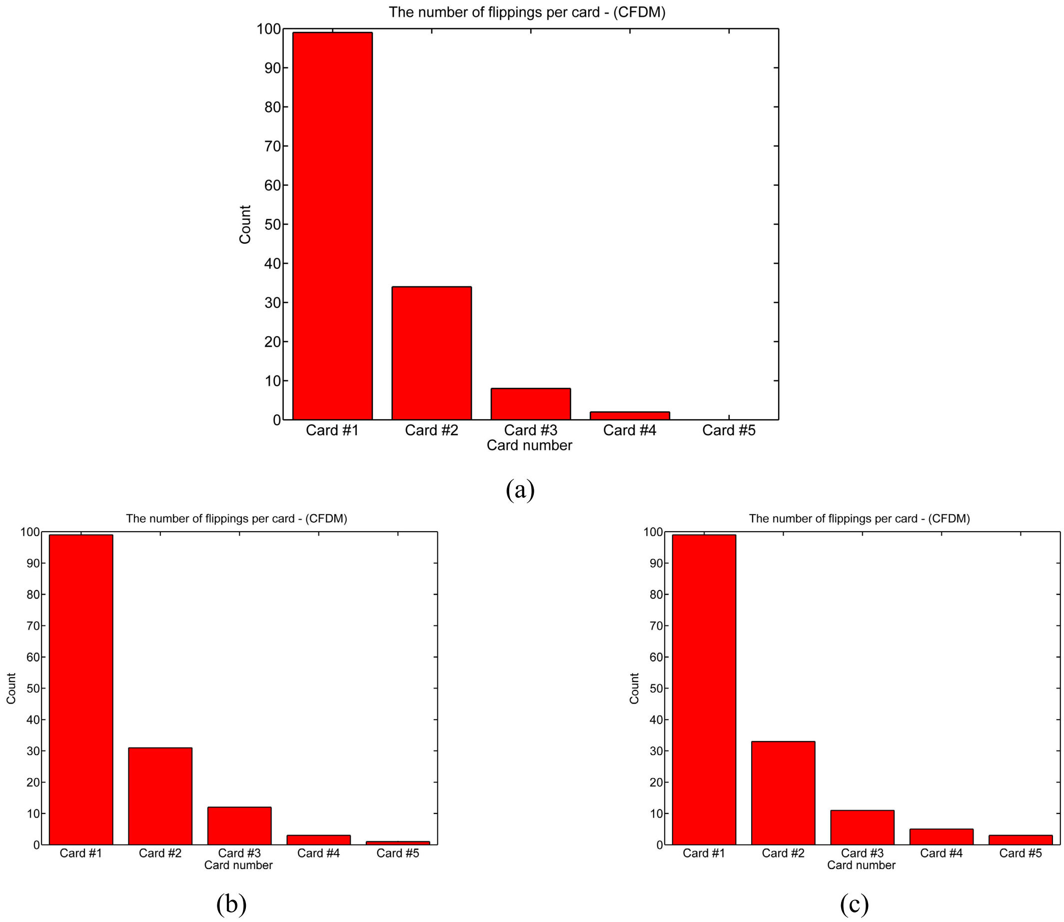


FIGURE 15. Number of flipping per card of the proposed CFDM technique. (a) first run, (b) second run, and (c) third run.

data rates. The third card has been flipped 8 times, 12 times, and 11 times. This is 23%, 38%, and 33% less compared with the second card, and 8%, 12%, and 11% of the first card.

So far, we can see the graduality of the decrease in the number of flips every time a new card is flipped. As this card represents the LiFi CDT, the decisions linked with the result of this card are impacted by the user speed, therefore, it is important to consider user mobility and its related measurements. The fourth card has been flipped 2 times, 3 times, and 5 times. This is 25%, 25%, and 45% of the previous card, and 1%, 3%, and 5% of the first card. The last card has been flipped 0 times in the first run, which means the WiFi capacity was never considered for any decision in this run. In the second run and third, this card has been flipped 1 time, and 3 times. This is 33% and 60% of the previous card, and 1% and 3% of the first card. This is a strong indication of how significantly low the possibility of flipping the fifth card is, no matter how many times the values of the previous card are changed.

This means the proposed method's maximum capacity is five criteria at most.

Among the most related works to the proposed technique, the use of multicriteria took place with various measurements and computations for the APA and HO process; however, none of them considered AP skipping. Figure 16 shows the number of AP skippings compared with the HO and AP assignment numbers.

As seen in the figure, both benchmark works perform the HO and AP assignment processes in the 99 iterations without performing any single AP skipping.

On the other hand, the proposed CFDM technique performs AP skipping almost half of the times over the total iterations, as 50 times the current AP was skipped in the first run as seen in Figure 16(a), 45 times in the second run as seen in Figure 16(b), and 48 times in the third run as seen in Figure 16(c). The HO and AP assignment process was performed as well by the proposed technique 49 times in the first run, 54 times in the second run, and 51 times in the third run.

The number of HO and AP assignment is almost equal to the AP skipping number in all cases. This is because the probability of choosing a range of values that trigger the either process is equal since the range of values in

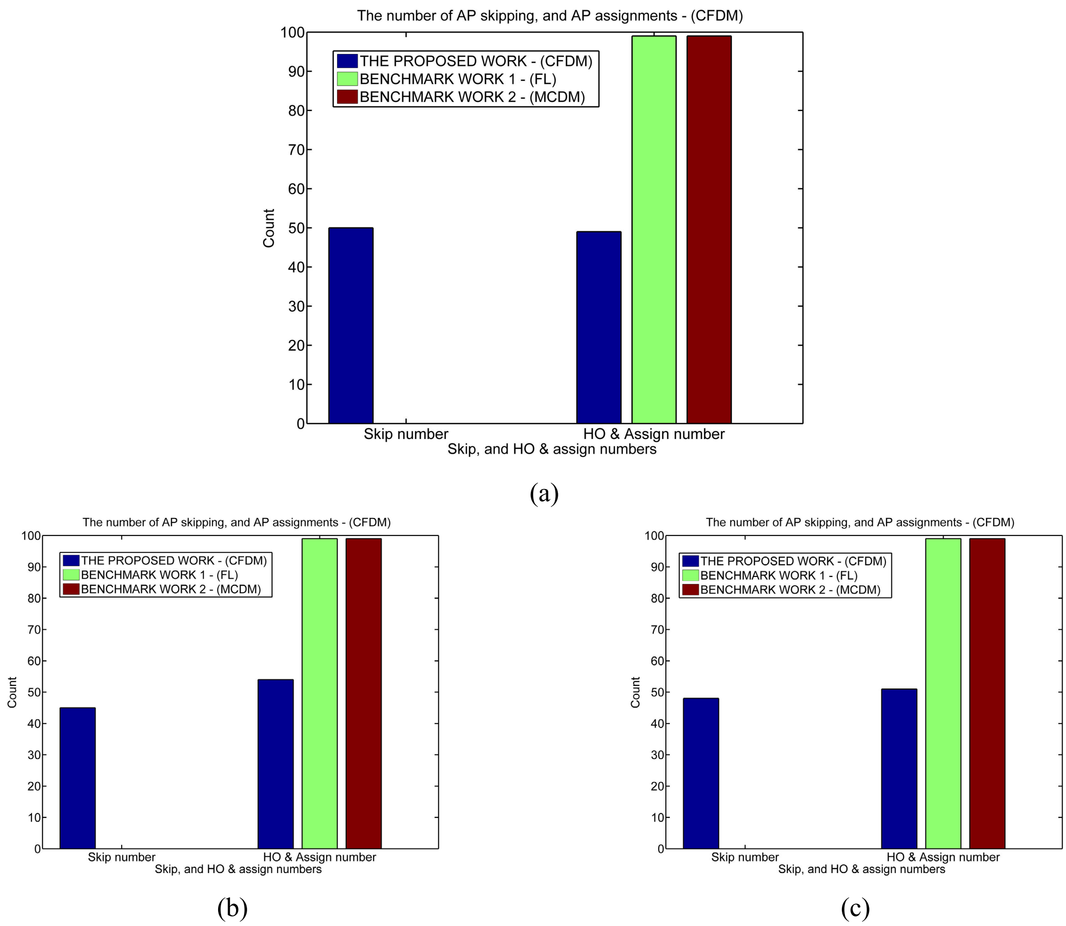


FIGURE 16. Number of AP skipping, HO and assignment. (a) first run, (b) second run, and (c) third run.

SEG_n 1 and SEG_n 3 have the same size of ranges., while the value of SEG_n 2 triggers the flipping the next card process only.

Apart from the results in Figure 16, the number of LiFi AP and WiFi AP assignments is another benefit of using the proposed CFDM method, which aims to assign the user to the LiFi network as possible before considering WiFi AP assignments. As can be seen in Figure 17, both benchmark works assign WiFi AP around 50 times as the average of all cases, and the rest is LiFi AP, while the proposed CFDM method assigns WiFi AP 12 times, 16 times, and 3 times in the first run, 2, and 3, as seen in Figure 17(a), (b), and (c), respectively, and the rest is LiFi AP over the 99 iterations. This is considered a big improvement for APA that could enhance the achieved data rates for users compared with the benchmark work 1 by 61% in the first run, 76% in the second run, and 115% in the third run. When comparing the proposed work with benchmark work 2, the improvements achieved are 97% in the first run, 84% in the second run, and 116% in the third run.

The higher number of LiFi AP assignments come from the AP skipping function in the proposed CFDM method, which results from low values of BC as well as the CC values. This could affect the delivered QoS to the users negatively.

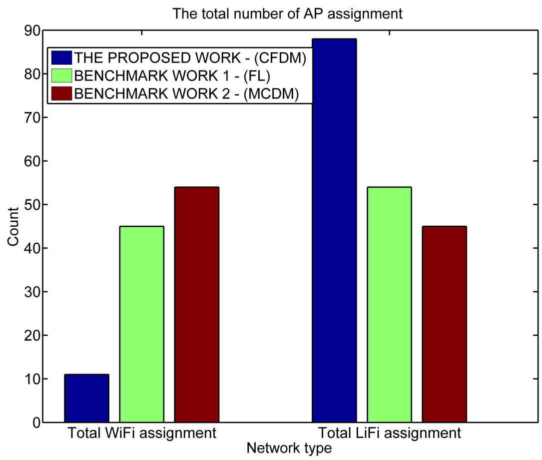
All the HOs and APAs that were achieved by the proposed method come from the high values of all criteria that guarantee higher QoS, including high data rates (high LiFi and WiFi capacities), longer times of connections (high LiFi CDT), and low shadowing rates (occurrence and occupation rates).

B. MAIN RESULTS

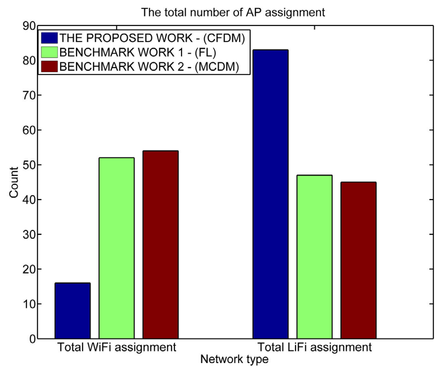
The results in this section are the VHO counts in addition to the number of HOs in each iteration. Switching probabilities are presented in each iteration as well in a percentage manner for the proposed work and the benchmark work.

The other important result is the complexity (FLOPS), as it represents the number of computational measurements for the used criteria. Figure 18 shows the VHO number throughout all iterations where the proposed method outperformed the benchmark greatly.

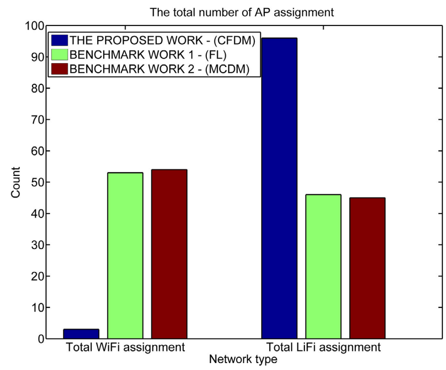
In Figure 18(a), the total number of VHO of the proposed CFDM at the end of the simulation is 8 times, 53 times by the



(a)



(b)



(c)

FIGURE 17. Number of assignments per network. (a) first run, (b) second run, and (c) third run.

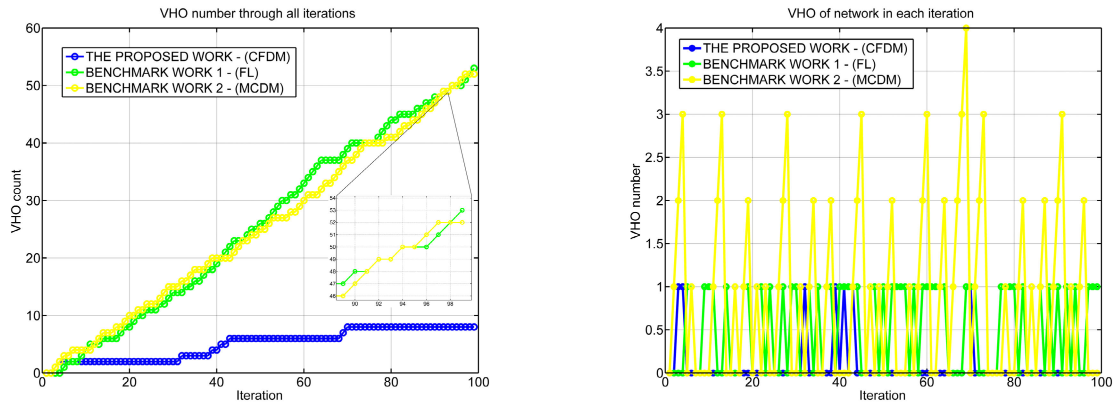
benchmark work 1 (FL), which is 85% less, and 52 times by the benchmark work 2 (MCDM), which is 84% better, as seen in Figure 18(a.1).

In the second run, the total VHO number of the CFDM is 14 times compared with 59 times by the FL, which is 76% better, and 48 times by the MCDM, which is 70% better. In the third run, the total VHO number of the CFDM is 6 times compared with 50 times by the FL, which is 88% better, and 58 times by the MCDM, which is 89% better. The HOs in each iteration of the first, second, and third run are shown in Figure 18(a.2), (b.2), and (c.2), where singular HOs can be recognized as well as sequential HOs.

Figure 19 shows the switching probabilities from an AP to another, and that is related to the HO process. In the first run, the switching probability of the proposed work is the lowest, which is considered the best, where the higher the value, the higher the chance of triggering a HO, followed by the FL method, and lastly, the MCDM, which has the lowest probability at the start of the simulation but gradually rises until it reaches 100% at the end of the simulation. In the second run, the switching probability of the proposed work is slightly higher than the FL method as well as in the third run, while the MCDM method achieves the same results in all iterations, as can be seen in Figure 19 (a.1), (b.1), and (c.1). Each of the benchmark works consists of using all the criteria at once in each iteration, while the proposed CFDM method uses one or more criteria in each iteration as cards, this leads to different values of switching probabilities for each card.

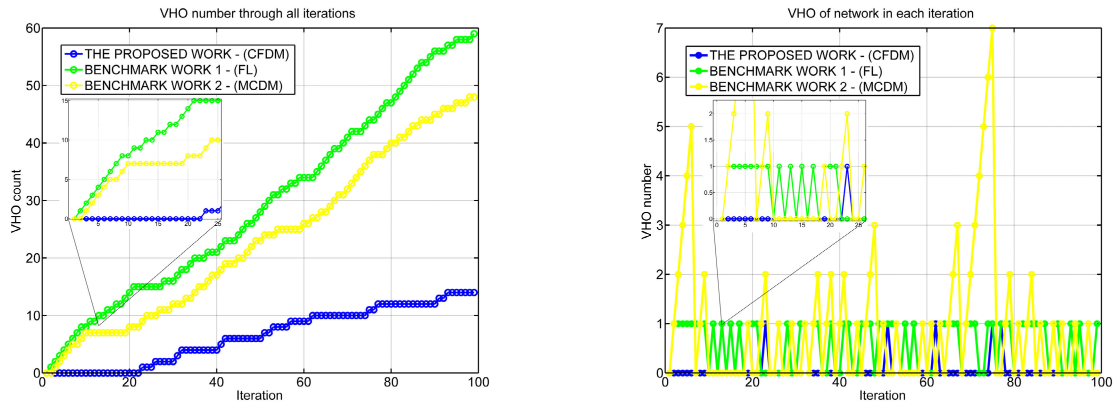
In Figure 19(a.2), (b.2), and (c.2), the individual values for each card are shown, where the values of both criteria that are related to the blockage are always the highest, including the occupation rate criteria and occurrence rate criteria, followed by the LiFi capacity criteria in all runs.

The value of LiFi CDT scored medium in all cases because, mostly, the LiFi CDT does not have a direct impact on the achieved data rate. The probability of WiFi always varies because it is the last card where the card is segmented to only two values, in addition to that, most of the time the last card does not have the chance of being flipped. When a card is not flipped, it does not pose any probability of switching for the current iteration and/or all iterations.



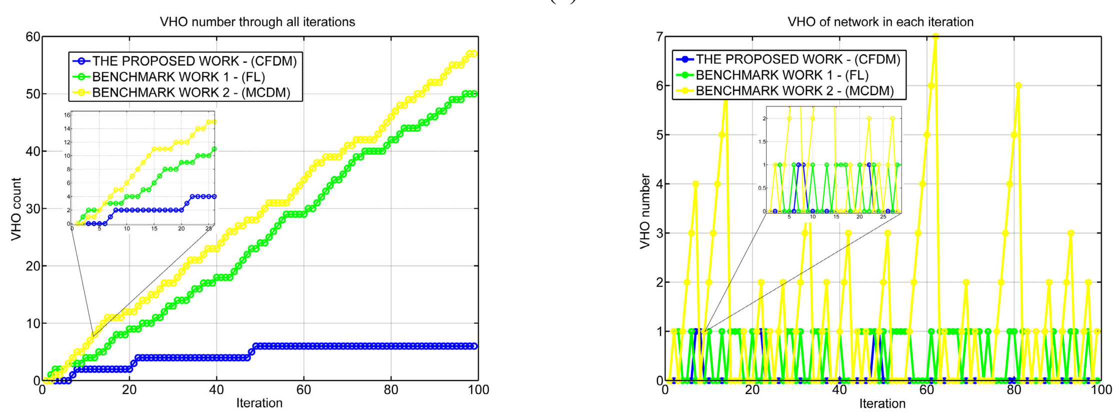
(1) (2)

(a)



(1) (2)

(b)



(1) (2)

(c)

FIGURE 18. Number of VHO in all iterations. (a) first run, (b) second run, and (c) third run.

The value of the switching probability of the proposed work has been calculated based on the achieved value of the card value, in addition to that value, an additional value is added to the switching probability every time a new card is flipped, which comes from the accumulated value of cards.

Figure 20 shows the complexity in all iterations where the proposed method achieved much lower complexity compared with the benchmark works. At the end of the iterations, the complexity for the CFDM reached 149, while the benchmark work reached 495, which is 69.89% better.

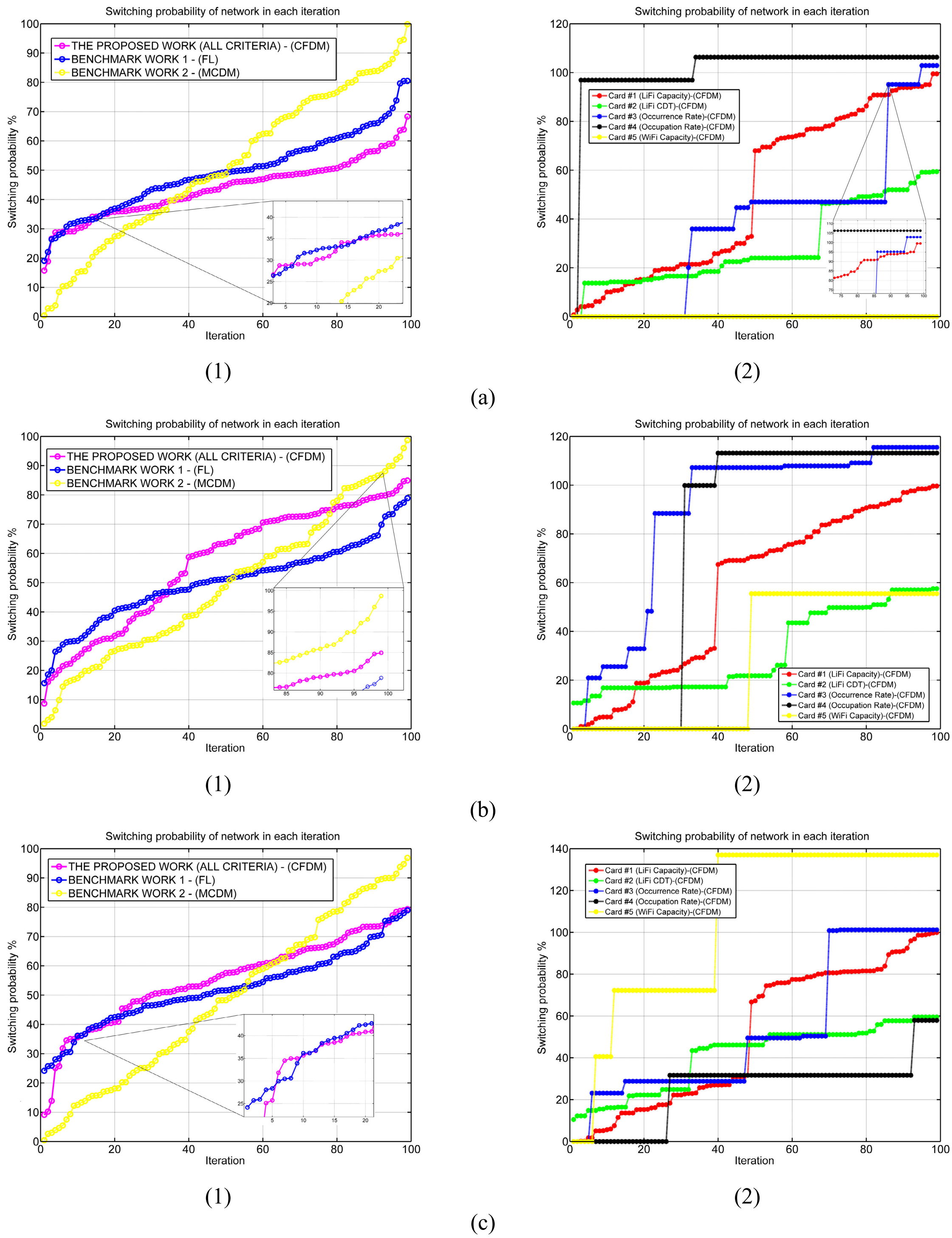


FIGURE 19. Switching probabilities of the proposed method vs the benchmark works, and the switching probability of each card in the proposed method. (a) first run, (b) second run, and (c) third run.

The values of both benchmark works are identical since the value of 1 FLOP = 1 criteria measurement and both of them consist of making measurements and computations for all criteria in each iteration, while the proposed method only performs the flipped card, which results in much lower computations. This is because when considering more criteria for making a decision, the computational complexity will increase.

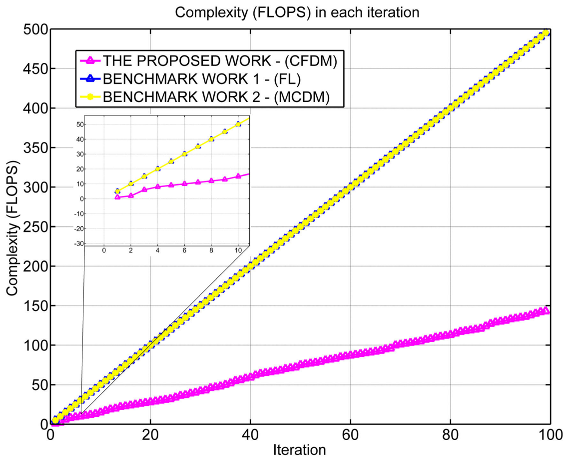


FIGURE 20. Complexity (FLOPS) of the proposed CFDM technique vs other works.

V. CONCLUSION

In this study, a new technique for APA and HO in hybrid LiFi networks has been proposed. The presented card flipping decision making CFDM method considers multiple criteria for making decisions. The AHP method is adopted to weight and prioritize the criteria. In addition, the CFDM was integrated with the AHP method for sorting and ranking all the considered criteria in the first stage, and the CFDM algorithm operates as the second stage. Each criterion is treated as a card, and each card is flipped and computed individually before considering the next card.

The proposed integrated AHP-CFDM is a new MCDM method and can be used in other applications and/or networks.

The proposed CFDM technique consists of three decisions, AP skipping, card flipping, and HO and AP assignment, where it allocates multiple segments and threshold values for each criterion for the sake of these decisions. This technique also considers the benefit and cost criteria when measuring criteria values, and it separates the criteria that are related to the LiFi network apart from the WiFi network in groups.

This work aims to reduce the vertical handovers and the computation complexity. This approach is novel and new to the LiFi research area with a new concept. An extensive comparison and simulations reported the significant performance of the CFDM technique over other recent approaches. The VHO, skipping rates, assignment rates, complexity, and switching probability have been calculated, analyzed, and discussed.

In the future work, an improved version of this technique will be developed, including mobility awareness, mobility patterns, user movement behavior, user data rate requirements, user density impact, and new criteria will be considered as well as applying the proposed technique to other networks besides the LiFi network. Other factors can be taken into account as well, such as network conditions, such as latency, resource allocation, stability, and user data rate requirements.

APPENDIX

Table 13 shows all the abbreviations used in this study.

TABLE 13. List of abbreviations.

Abbreviation	Description
APA	access point assignment
HO	handover
MCDM	multicriteria decision-making
AP	access point
CFDM	card-flipping decision making
AHP	analytic hierarchy process
CR	consistency ratio
RGMM	rank-based maximum likelihood method
WGMM	Weighted Geometric Mean Method
RF	radio frequency
IM	intensity modulation
DD	direct detection
HHO	horizontal handover
VHO	vertical handover
I-VHO	immediate vertical handover
LB	load balancing
CCI	co-channel interference
LOS	line-of-sight
MPTCP	multipath transmission control protocol
FAHP	fuzzy analytic hierarchy process
TOPSIS	technique for order preference by similarity to ideal solution
FLOPS	floating-point operations
FL	fuzzy logic
MCDA	multicriteria decision analysis
VIKOR	VIekriteri-Jumsko KOmpromisno Rangiranje
CSI	channel state information
CDT	Cell dwell time
ANN	artificial neural network
SINR	signal-to-interference-plus-noise ratio
RSS	received signal strength
MALB-KKOA	mobility aware LB using Kho–Kho optimization algorithm
MA	multiple AP associations
SA	one AP association
MI	mobility index
HOM	HO margin
TTT	time to trigger
IVM	information value model
IHM	intelligent HO model
DL	deep learning
SNR	signal-to-noise ratio
BER	bit error rate
AADR	average available data rate
LA	link aggregation
RL	reinforcement learning
ORWP	orientation-based random waypoint
HORWP	hotspot ORWP
USP	user selection procedure
RSRP	reference signal received power
ROI	received optical signal intensity
CAP	closest AP
MCG	maximum channel gain
TPHM-APT	three-stage HO management and AP transition
MF	membership functions
DK	domain knowledge
CXY	Complexity
MOB	Mobility
TAA	threshold-based access algorithm
RAA	random-access algorithm
EXP3	exploration and exploitation'
ELP	exponentially-weighted algorithm with linear programming"
Exh-LA	exhaustive search with LA
PD	photon detectors
CU	central unit
TDMA	time division multi-access
OFDMA	orthogonal frequency division multiplexing access
PP	ping-pong
BS	base station
VL	visible light

TABLE 13. ***(Continued.)*** **List of abbreviations.**

SC	small cell
PSD	power spectral density
D-VHO	dwell vertical handover
PPP	Poisson point process
CR	consistency Ratio
AHP-S*	AHP Consensus Indicator
CJ	criterion judgment
PCM	pairwise comparison matrix
CM	consolidation matrix
AIJ	aggregate of individual judgements
AIP	aggregate of individual priorities
EVM	earned value management
BC	benefit criteria
CC	cost criteria

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