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Machine Learning and Reinforcement Learning for Load Balancing and Handover Management in Hybrid LiFi/WiFi Networks: A Comprehensive Survey

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Abstract: Hybrid Light Fidelity (LiFi) and Wireless Fidelity (WiFi) networks combine two links with different strengths. LiFi can support high indoor data rates, while WiFi provides wider radio coverage when the optical link is weak or blocked. The main difficulty is that users do not remain in fixed or ideal positions. As users move, traffic changes, and access points (APs) become unevenly loaded, the network has to decide when to keep a user on the current link and when to switch the user to another AP. This review discusses machine learning (ML) and reinforcement learning (RL) methods used for AP selection, load balancing, and handover management in hybrid LiFi/WiFi networks. ML methods usually learn from channel quality, traffic load, user demand, and mobility information, whereas RL methods are used when a switching decision has later effects on throughput, load balance, or handover frequency. The reviewed studies indicate that learning-based methods can perform better than fixed-threshold or rule-based schemes in dynamic indoor settings. Even so, their results are still affected by the training data, network layout, reward design, and coordination among APs. More practical evaluation settings and lighter learning models are therefore needed before these methods can be used widely in real indoor deployments.

Keywords: Deep Learning, Reinforcement Learning, LiFi/WiFi Hybrid Network, Load Balancing, Signal to Interference plus Noise Ratio (SINR)

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1. INTRODUCTION

Wireless communication systems have moved quickly from fifth-generation (5G) deployment and standardization toward early studies of sixth-generation (6G) networks [1-3]. In this transition, heterogeneous network management has become a more difficult problem, especially when load balancing and handover decisions must be made across different access technologies [4-6]. Hybrid WiFi/LiFi networking is one possible response to this problem, since WiFi offers wide-area radio coverage while LiFi can provide high-capacity optical links in indoor environments [7-10].

Load balancing is important because uneven traffic distribution can leave some access points (APs) overloaded while others remain underused. In hybrid LiFi/WiFi systems, this imbalance may lower throughput, increase latency, and reduce the quality of the user experience [13-14]. Early load balancing schemes often relied on received signal strength (RSS) or signal-to-interference-plus-noise ratio (SINR). Although these indicators are useful, they do not fully capture the changing conditions of a hybrid indoor network. User movement, traffic demand, channel variation, and quality of service (QoS) requirements can all affect the best AP choice, which makes fixed or purely signal-based decisions less reliable [11-12].

Handover is also more difficult in a hybrid LiFi/WiFi system than in a single-radio network. A user may move out of a LiFi cell, enter a shadowed area, or fall back to WiFi when the optical link becomes weak. In these cases, the network has to keep the session active while avoiding unnecessary switching [15-16]. Conventional handover rules based on fixed thresholds or hysteresis timers can still be useful in simple situations, but they often react only after the link quality has already changed. They also treat LiFi and WiFi links in a similar way, although the two links behave differently in terms of coverage, blockage, and mobility. This can lead to repeated handovers, extra signaling, and lower quality of service [17-18].

Because of these limitations, recent work has started to use machine learning (ML) and reinforcement learning (RL) for load balancing and handover control in hybrid LiFi/WiFi networks. ML methods are useful when the network can learn from examples of user movement, channel quality, traffic load, and access point (AP) association. Models such as artificial neural networks (ANNs), deep neural networks (DNNs), convolutional neural networks (CNNs), support vector machines (SVMs), and sequence-aware neural networks have therefore been studied for AP selection, load balancing, and handover prediction. Their main role is to turn network observations into better switching or association decisions.

RL is useful for a related but slightly different reason. In many cases, the best AP decision is not the one that gives the highest immediate signal strength, but the one that produces better performance over the next few moments of movement and traffic change. RL methods, including Q-learning, deep reinforcement learning, proximal policy optimization (PPO), and multi-agent RL, learn this type of policy through interaction with the network environment. They can adjust switching and load-allocation actions according to rewards such as throughput, latency, handover frequency, or load balance.

Existing studies report that ML and RL based methods can improve load distribution, reduce avoidable handovers, increase throughput, and lower latency in hybrid LiFi/WiFi networks. These gains, however, should be read with some caution. Many methods are still evaluated under specific simulation settings, and their performance may change with algorithm complexity, training data, AP density, indoor layout, mobility pattern, and reward design. For this reason, this paper reviews not only the reported improvements of ML and RL methods, but also the conditions under which they are likely to work well. The review connects the learning mechanisms with practical AP-selection, traffic-distribution, and mobility-management problems in hybrid LiFi/WiFi networks [19].

The main contributions of this survey are summarized as follows:

1. **Clarifying the network problem:** This review first discusses why load balancing and handover are difficult in hybrid LiFi/WiFi networks. The discussion covers AP congestion, user mobility, channel variation, blockage, and QoS requirements.
2. **Reviewing learning-based solutions:** Existing ML and RL methods are grouped according to how they make AP-selection, load-balancing, and handover decisions. This helps show the difference between methods that mainly learn from data and methods that learn through interaction with the network.
3. **Comparing reported performance:** The reviewed studies are compared using common indicators such as throughput, handover reduction, latency, computational complexity, adaptability, and practical deployment constraints.
4. **Identifying remaining gaps:** The review also points out issues that are not yet fully resolved, including transfer learning, multi-agent coordination, edge-assisted intelligence, scalability, and generalization across different indoor environments.

The rest of this paper is organized as follows. Section 2 introduces the hybrid LiFi/WiFi network model and the related channel model used to describe optical and radio links. Section 3 reviews ML based approaches for load balancing and handover management, while Section 4 discusses RL based approaches. Section 5 summarizes and compares the reviewed methods, discusses their limitations, and identifies possible research directions. Section 6 concludes the paper.

2. CHANNEL MODEL

The foundation for exploring WiFi/LiFi switching strategies lies in establishing accurate channel models for both LiFi and WiFi technologies [20-27]. These models are used to calculate key network performance indicators, including signal-to-noise ratio (SNR), throughput, and data transmission rate, which significantly impact user communication quality. The indoor WiFi channel is commonly modeled as a Rayleigh fading channel, with the typical path loss expression given by [22]:

$$PL[dB] = A\log_{10}(d[m]) + B + C\log_{10}(\frac{f_c[GHz]}{5}) \quad (1)$$

In equation (1), the distance between the Wi-Fi signal transmitter and the terminal device is expressed by *d*, and the unit is meters (*m*); the carrier frequency *fc* is 2.4*GHz*, and the specific values of *A*, *B*, and *C* depend on the communication model used. Since WiFi serves as an auxiliary supplement to Li-Fi in home networks, only one WiFi access point is usually deployed. Hence, there is no need to consider the mutual influence between channels. The SNR of the WiFi AP signal received by the user depends on various factors during the WiFi channel transmission process, including temperature, the transmit power of the signal transmitter, and the available bandwidth. The signal-to-noise ratio and data rate available to user u connected to the *a-th* Wi-Fi are [24]:

$$SNR_{u,a} = \frac{P_R G_{des}}{P_n} \quad (2)$$

$$R_{u,a} = B_W \log_2(1 + SNR_{u,a}) \quad (3)$$

In equations (2) and (3), the B_W, P_R, and *Pn* are the bandwidth used for WiFi communication, the transmit power of WiFi-AP, and the noise power, respectively. The path gain is expressed as [25]:

$$G_{des} = 10^{-PL[dB]/10} \quad (4)$$

In equation (3), G_{des} represents the path gain. In the optical channel model, shown in Figure 1, the impact of the front-end equipment filter is not considered, and only the channel gain of light in free space is considered. The commonly used optical channel model is the light propagation model under a line-of-sight link (LoS). The expression of the channel gain between LiFi-AP and the target user is [28]:

$$G_{u,b} = \frac{A_p(m+1)h^{m+1}}{2\pi}(r_l^2 + h^2) \quad (5)$$

In equation (5), $G_{u,b}$ is the channel gain between user *u* and LiFi-AP$_b$, *m* is the Lambertian radiation series; *Ap* is the effective receiving area of the receiver photodetector; RL is the horizontal distance between the user and AP; *h* is the vertical distance between the user and the AP. Different channels have different gain expressions. The most commonly used in-home VLC communications is the LoS optical channel model.

For a given user u connected to the *b-th* LiFi-AP, the signal-to-interference ratio of the link calculated from the user's channel gain can be expressed as $SINR_{u,b}$. The data rate available when user u connects to the *b-th* LiFi-AP is [29]:

$$SINR_{u,b} = \frac{\left(G_{u,b}P_{lf}\right)^2}{N_{lf}B_L + \sum_{other}\left(G_{u,b}P_{lf}\right)^2} \tag{6}$$

$$R_{u,b} = \frac{B_L}{2}\log_2\left(1 + SINR_{u,b}\right) \tag{7}$$

In equation (6), N_{lf} represents noise power spectral density, B_L represents the used bandwidth of LiFi-AP, P_{lf} represents LiFi transmit power. In equation (7), $R_{u,b}$ represents the data rate obtained by user u in LiFi-b class.

Research on handover between heterogeneous networks is fundamentally based on LiFi and WiFi channel models. Particularly during user movement, when users transition from the coverage of one AP to another, the handover algorithm makes network switching decisions. The design of handover algorithms requires careful balance among latency, throughput, and QoS [29-32]. Therefore, ensuring seamless user connectivity in heterogeneous networks and controlling load balancing between APs through efficient handover mechanisms remains essential to current research.

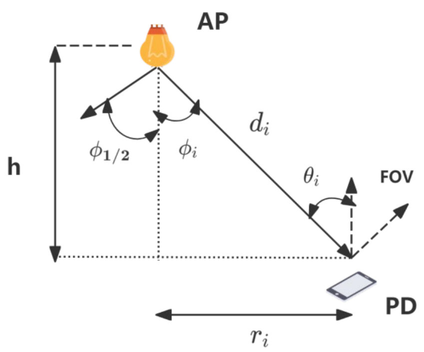

Figure 1. LoS-based indoor LiFi optical propagation model used to calculate AP-user channel gain and SINR, where d_i denotes the propagation distance, ϕ_i and θ_i denote the irradiance and incidence angles, respectively, and PD denotes the photodetector. Adapted from the indoor LiFi/VLC channel models in [1, 20, 23, 26-27].

3. APPLICATION OF DIFFERENT MACHINE LEARNING METHODS IN HYBRID NETWORKS

An in-depth investigation of the handover problem in LiFi/WiFi hybrid networks reveals that user behavior in indoor environments and varying network requirements significantly influence handover frequency [33]. Frequent handovers occur when users rapidly transition from LiFi coverage areas to WiFi access points, often leading to WiFi traffic overload and channel congestion. This congestion degrades both QoS and QoE [34]. To address this issue, researchers have proposed ML classification algorithms to optimize device switching decisions between LiFi and WiFi networks [35]. This approach adjusts the switching strategy by setting a network preference coefficient that evaluates communication quality, resource availability, and user mobility [36]. Recent user-centric and learning-enabled studies extend this direction to MPTCP-enabled resource allocation and throughput-handover trade-off settings [37]. Table 1 presents a summary of key research on ML applications in hybrid networks.

In [38], the authors investigated machine learning strategies for load balancing in LiFi/WiFi hybrid systems, aiming to improve QoS and prevent degradation of client experience caused by overloaded access points. They employed ANN-based or related learning approaches to process user and network-state data, enabling the network to allocate resources intelligently and balance client loads across access points [39]. These learning-based approaches outperform traditional RSS-based load balancing methods across key metrics. While they may not always excel in load distribution compared to RSS methods, they effectively reduce network congestion, increase throughput, and decrease latency. This work has established the foundation for applying machine learning techniques in hybrid network load management and has become an important reference for subsequent studies.

In [40], a hybrid LiFi and WiFi approach was proposed to enable collaborative decision-making using SVM. By analyzing the relationship between blocking parameters across adjacent time periods, the system can achieve improved performance even when blocking parameters are not accurately available. This method leverages SVM's classification and prediction capabilities to make intelligent decisions with limited data, thereby optimizing resource allocation.

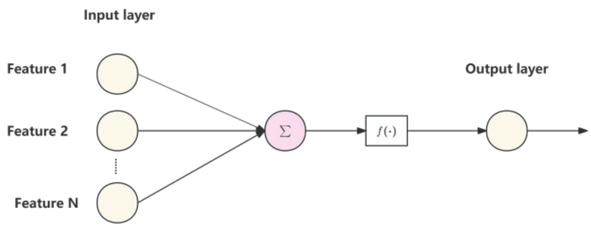

Figure 2. ANN-based load-balancing architecture for hybrid LiFi/WiFi networks. Input features such as channel quality, AP load, user mobility, and resource availability are processed through hidden layers to produce AP-selection decisions

Meanwhile, in [41], handover strategies based on ANN or related learning models were implemented, considering factors such as client mobility, channel quality, and resource availability. Figure 2 illustrates the application framework of the ANN model for load balancing in LiFi/WiFi hybrid networks. To more accurately simulate user movement, these approaches incorporate mobility-aware features to characterize user movement patterns. Compared to RSS-based and direction prediction-based handover strategies, this approach significantly improves network throughput for clients. Experimental data demonstrates a 260% increase in throughput over the RSS method and a 50% improvement compared to the trajectory-based handover strategy.

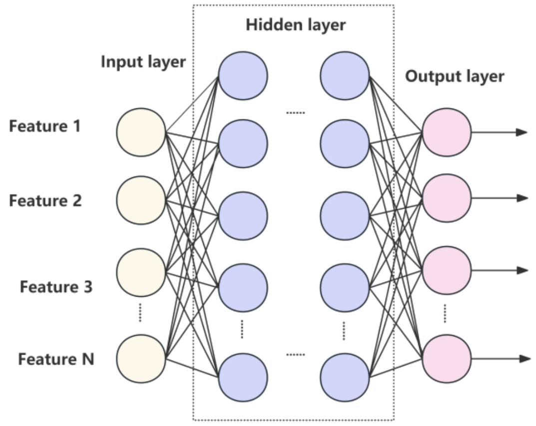

Figure 3. A hybrid LiFi/WiFi network handover and load balancing framework based on deep neural networks. Adapted from [24], [27].

In related studies, [42-46] explored the application of DNNs, CNNs, and proactive deep learning models in LiFi or hybrid networks. Figure 3 illustrates the structure of the DNN model and its application in LiFi/WiFi hybrid networks. Compared to traditional ANNs, DNNs offer enhanced feature extraction capabilities and greater learning capacity through additional hidden layers. Figure 4 shows the CNN model, which introduces a convolutional layer before the fully connected layer of the DNN to improve data feature extraction. These studies indicate that DNN/CNN-style models are most useful when AP selection depends on nonlinear channel, mobility, or spatial-state interactions.

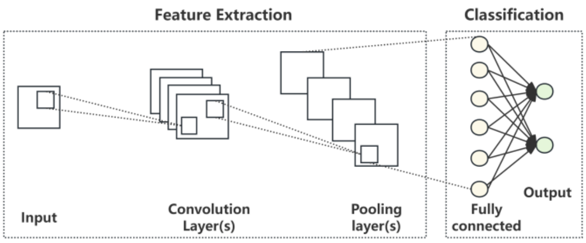

Figure 4. CNN-based feature extraction model for hybrid network decision-making, including convolutional, pooling, fully connected, and output layers. Adapted from [42], [45].

In [47], a switching strategy based on dual ANNs was proposed, treating the switching problem as a classification task. This model uses features such as device orientation, movement, and channel conditions as input variables for network training. After training, the model was tested in indoor environments, with experimental results showing switching accuracy exceeding 95%. Compared to using a single ANN, the dual ANN approach improved network throughput by 20% and reduced switching frequency by 59%. By more accurately identifying switching opportunities, this method minimizes the network resource consumption associated with frequent switching, thereby enhancing overall service quality.

In [48], the authors introduced an adaptive target-condition neural network to reduce load imbalance caused by changes in the number of users in hybrid networks. A useful feature of this approach is that it can assign users to suitable APs by considering both data-rate requirements and the demands of other users, without requiring the model to be retrained for each new condition. Compared with a conventional DNN-based scheme, the adaptive neural model was reported to improve network throughput while keeping the system design relatively simple.

In [49], a mobility- and multipath-aware learning method was proposed for heterogeneous LiFi/WiFi networks. The method incorporates user movement, AP load, and link-condition information into the switching decision, allowing the network to respond more effectively when devices move across coverage areas. The reviewed study reported fewer handovers, better energy efficiency, and lower latency, which suggests that mobility-aware learning can help reduce the performance degradation caused by frequent AP switching.

The study in [50] proposed a deep neural network-based handover approach for hybrid LiFi and WiFi networks. The model did not only use basic network information. It also considered the direction of the user device and the angle between the device and the LED. These factors make sense in a LiFi link, because the received signal can change when the device is turned or tilted. At the same time, adding these inputs also makes the model harder to train and increases the computation needed. These improvements contribute to better network QoS and user experience in complex environments.

Overall, ML-based methods improve handover accuracy, throughput, and switching efficiency in hybrid LiFi/WiFi networks, but their applicability depends on the dominant scenario features. ANN and SVM are suitable for stable and low-dimensional AP-selection problems because they provide low-complexity and fast decisions. DNN and hybrid ANN-DNN models are more effective when handover decisions depend on nonlinear interactions among channel quality, AP load, user orientation, traffic demand, and mobility. CNN-based models are preferable when the network state has spatial structure, such as AP/user distribution or interference maps, whereas mobility-aware models are more suitable for handover because they can exploit temporal user behavior and reduce ping-pong switching. However, most ML methods still depend on representative training data and may require retraining when the deployment scenario changes, especially under concept drift in dynamic LiFi environments [51]. Recent studies further extend these designs toward GNN-based load balancing and service- or energy-aware differentiation [52-53]. This limitation motivates the use of RL methods for more adaptive decision-making in dynamic hybrid networks.

4. THE APPLICATION OF REINFORCEMENT LEARNING TECHNOLOGY IN HYBRID NETWORKS

Reinforcement Learning (RL) technology is frequently employed to address load balancing problems in hybrid networks, providing practical solutions for maximizing system performance. RL offers a different way to approach load balancing and throughput optimization. Instead of relying on fixed rules, an RL agent learns from its interaction with the network environment. Through repeated trial and error, it adjusts its policy according to the rewards obtained from different load allocation or AP-switching decisions. Its adaptive and flexible nature makes it particularly well-suited for optimizing performance in complex and dynamic network environments. Table 2 summarizes key RL research methods in hybrid networks.

For instance, in [54-55], Q-learning-based algorithms were proposed to tackle load balancing or handover-parameter optimization problems in hybrid radio-optical networks. These methods leverage Q-value learning, where RL is used to develop optimal AP allocation or handover-trigger strategies. After each action, a reward is calculated by determining the Q-value of each potential action, allowing the system to identify the action with the highest reward function. Applying Q-learning enhances network performance by reducing unnecessary handovers and optimizing resource allocation, thereby improving user experience. As a model-free reinforcement learning algorithm, Q-learning is effective in dynamic and uncertain network environments, learning optimal actions through a balance of exploration and exploitation. However, Q-learning encounters stability issues in environments with large action spaces. Consequently, it is better suited for simpler environments with smaller action spaces.

Building upon tabular RL, deep reinforcement learning-based user association was introduced in [56] for hybrid LiFi/WiFi indoor networks. By using neural networks to represent the association policy or value function, deep RL improves scalability compared with tabular Q-learning in larger state spaces. This demonstrates the effectiveness of deep RL in optimizing AP association and resource allocation under complex network conditions.

Ahmed's research team has made substantial contributions to applying RL methods for solving optimization problems in hybrid networks. Following their work with Q-learning, related studies explored near-optimal and sequential RL-based load-balancing strategies to maximize system throughput and user satisfaction [57-58]. These algorithms evaluate the effectiveness of each action using different reward functions, optimizing network resource allocation and improving user experience. This intelligent RL-based approach enhances overall network performance and user satisfaction.

While Trust Region Policy Optimization (TRPO) offers better stability than Q-learning and DQN, addressing issues with unstable training due to large action spaces, it increases the complexity of the gradient strategy and lengthens training time [59]. Consequently, TRPO is more suitable for environments with fixed users and less effective in dynamic environments with user mobility.

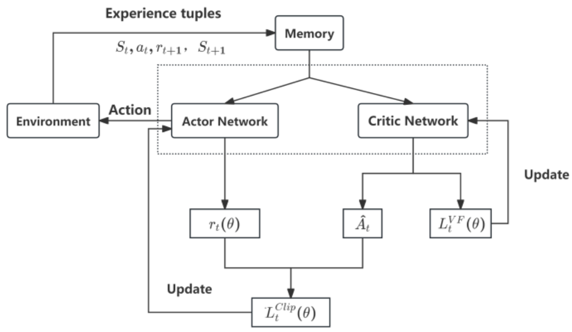

Figure 5. PPO-based reinforcement-learning framework for AP selection in hybrid LiFi/WiFi networks. The agent observes channel quality, AP load, user mobility, and QoS state, selects an association or handover action, and updates the policy using reward signals that balance throughput [45].

To address the challenges of high computational complexity and long training times in policy-gradient RL, [60] proposed a resource allocation method using PPO, as shown in Figure 5. This approach employs pruning to eliminate suboptimal handover strategies and optimize AP distribution. Compared to TRPO, PPO significantly reduces computational complexity, limits the number of reuse strategies, and improves algorithm stability by pruning negative strategies. The study considers network capacity limits and user mobility patterns, with particular attention to how the number of users affects single-user throughput for both mobile and fixed users.

While TRPO excels in user satisfaction in stable user environments, PPO offers superior computational efficiency and adaptability in dynamic, rapidly changing user scenarios. Additionally, [61] proposed a multi-agent RL method to optimize resource allocation. Compared to RSS-based solutions, this approach improves average throughput by 37% and average user satisfaction by 56%.

In recent years, researchers have turned to hybrid methods that combine multiple technologies to tackle the growing complexity of network environments and evolving user needs. These approaches aim to overcome the limitations of traditional single technologies in dynamic scenarios, such as new device access, vertical handoff delays, and user mobility prediction.

Three hybrid methods were proposed in [62], integrating RL with other technologies to address these challenges. These methods combine RL with transfer learning, Q-learning optimization, and trajectory classification models, enhancing network performance while maintaining system stability and adaptability.

Specifically, [62] applied transfer learning to resource allotment in dynamic hybrid WiFi/LiFi communication systems. In [63], RL was used for resource allocation in dynamic aggregated WiFi/VLC heterogeneous networks. Q-learning can also be used to optimize handover trigger time and reduce unnecessary vertical handoffs, as discussed earlier for handover-parameter optimization. In [64], a prediction-model-assisted RL algorithm used trajectory information to support handover decision-making in hybrid LiFi/WiFi networks. Other recent RL- or AI-driven studies extend handover management to trajectory prediction, load balancing, and ultra-dense 5G/6G settings [65-67].

Hybrid methods are helpful because one model may not be enough for all parts of the LiFi/WiFi switching problem. A supervised learning model can learn common patterns from past data, such as user movement, traffic load, and channel quality. Reinforcement learning can then help when the effect of a decision is not immediate. For example, one handover may reduce congestion now, but it may also cause another handover shortly after. For this reason, hybrid methods are useful when load balancing, mobility, and handover stability need to be considered together.

5. DISCUSSION

The studies reviewed in this paper show that ML and RL can help improve load balancing and handover control in hybrid LiFi/WiFi networks. However, the results are not the same in every case, because each model works better under different network conditions. This section compares the reported results, explains where different model types are more suitable, and points out the main limitations. Table 3 lists the key reported metrics from representative studies.

5.1 Summary of main research results

The literature highlights the effectiveness of machine learning technologies, including ANNs, DNNs, CNNs, and LSTM networks, in improving load balancing and handover decisions in hybrid LiFi/WiFi networks. Compared with traditional methods, such as RSS-based approaches, these algorithms demonstrate enhanced performance in throughput, latency, and user satisfaction metrics. Furthermore, the integration of reinforcement learning algorithms, including Q-learning, DQN, TRPO, and PPO, further enhances the adaptability and robustness of network management strategies.

5.2 Comparison with existing works

Unlike traditional load balancing and switching methods, ML and RL-based approaches offer superior adaptability and performance in complex, dynamic network environments, but their advantages depend strongly on the structure of the decision problem. ANN and SVM models perform well in relatively stable AP-selection scenarios because their low-complexity decision surfaces are sufficient when the inputs are limited to RSS, SINR, AP load, or coarse mobility indicators. DNN and CNN models become more effective when the decision depends on nonlinear interactions among channel quality, user orientation, blockage, interference, and AP distribution; CNNs are especially useful when the network state can be represented as spatial features. Mobility-aware and sequence-aware models are preferable for handover scenarios because temporal or trajectory information helps suppress ping-pong switching and anticipate user movement.

RL methods are more appropriate when a handover decision has delayed consequences, since reward functions can jointly encode throughput, load balance, user satisfaction, and handover cost. However, this flexibility also makes RL sensitive to reward design, convergence time, and state-space size. Therefore, no single model family is universally superior; the appropriate method depends on whether the deployment is static or mobile, low-dimensional or high-dimensional, centralized or distributed, and optimized for throughput, handover stability, energy efficiency, or QoS.

5.3 Limitations and Challenges

Although the reported results are useful, there are still some practical problems. The first one is the cost of running these models. Many ML and RL methods need a large amount of training data and a long training time, especially when the model has to consider user movement, channel changes, AP load, and QoS at the same time. This may not be a serious problem in offline simulation, but it becomes more important if the model needs to be updated often or used on edge devices with limited computing power.

Another problem is that the reported performance may not hold under all network conditions. Some methods work well in the tested scenario, but it is still unclear how they behave when traffic changes suddenly, when a LiFi link is blocked, when many users move at the same time, or when the channel changes quickly [68]. It is also hard to compare studies directly. Different papers use different room sizes, AP densities, mobility models, traffic settings, and reward functions, so two methods may report similar throughput or handover gains but actually be tested under quite different conditions.

5.4 Future research directions

Future studies should move closer to the conditions found in real indoor LiFi/WiFi networks. A model that works well in simulation may still be difficult to use if it requires too much memory, long training time, or frequent retraining.

One practical issue is model size. Handover and load-balancing decisions often have to be made quickly, especially when users move or when a LiFi link is blocked. For this reason, lightweight neural networks, pruning-based model compression [69], and simpler inference structures deserve more attention. These methods can reduce computation and delay without changing the basic goal of AP selection.

RL-based methods also need to learn faster. In many studies, the agent requires many interactions with the environment before it finds a useful policy. This is acceptable in offline simulation, but it is harder to accept in a live network. Transfer learning may reduce this burden by reusing knowledge from a similar indoor setting, while meta-learning may help the model adapt when user movement, AP density, or traffic demand changes.

Network control technologies can also support learning-based methods, but they should not be added only for novelty. Edge computing is useful when decisions need to be made near the user with low delay. Software-defined networking (SDN) can help coordinate AP selection and load distribution across the network [70]. Blockchain may be useful for authentication or decentralized resource management, but its delay and computational cost must be justified.

In future work, throughput and handover reduction should not be the only targets. A practical method also needs to be lightweight, explainable, comparable across studies, and reliable under different indoor layouts and user densities.

6. CONCLUSION

This review examined how machine learning and reinforcement learning have been used for load balancing and handover management in hybrid LiFi/WiFi networks. The literature suggests that learning-based methods are useful because they can make decisions from more than one signal indicator, including channel quality, user movement, AP load, and traffic demand. This gives them an advantage over fixed-threshold schemes in dynamic indoor environments. At the same time, the results reported in different studies are not always easy to compare, since the test scenarios, mobility models, reward functions, and evaluation metrics are often different. For practical deployment, the main task is no longer only to improve throughput or reduce handovers, but to develop methods that are lighter, easier to explain, and more reliable across different indoor network conditions.

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Table 1. Research on User Connection Classification Based on Machine Learning

Reference	Method	Results	Accuracy
Alotaibi et al., 2015 [38], Farrag M et al., 2023 [39]	ANN-based load balancing	Reduced latency and improved throughput compared to the RSS strategy.	72.2%
Ji et al., 2019 [40]	SVM-based load balancing	Superior performance over traditional RSS methods.	78.1%
Wu et al., 2020[41] Wang et al., 2023 [14]	ANN + extended input features	Compared to RSS: 260% throughput improvement; Compared to trajectory prediction: 50% throughput improvement.	95.3%
Ma et al., 2022 [47]	Dual ANN collaborative decision-making	Compared to a single ANN: 20% throughput improvement, 59% reduction in handover frequency.	96.7%
A. Rfaoui et al., 2021 [43] Nashin et al., 2023 [42]	DNN vs. CNN comparison	LiFi environment: DNN outperforms CNN; WiFi environment: CNN outperforms DNN	—
Ji et al., 2024[48]	Adaptive Temporal Convolutional Neural Network (A-TCNN)	Reduced system complexity and 45% throughput improvement.	91.8%%
Arunkumar et al., 2024[49]	LSTM + Heuristic optimization algorithm (STIO)	Reduced handover frequency, improved energy efficiency, and reduced latency to 0.113ms.	93.7%
Khan et al., 2024[50]	ANN-DNN hybrid neural network	Handover frequency reduced by 55.21%-67.15%, and throughput improved by 8.58%-38.5%.	97%

Table 2. Research on User Connection Classification Based on Machine Learning

Reference	Method	Results	Complexity
R. Ahmad et al., 2020[55]	Q-learning + Gradient Descent	Marginal improvement in system throughput and reduced handover frequency compared to RSS	Low
R. Ahmad et al., 2022[57]	The RL method of TRPO	Compared with RSS, the system throughput has increased by 23%, and the average user satisfaction can reach 96%.	High
R. Ahmad et al., 2022[58]	Translating the Resource Allocation Method with Sequential Balance	Compared with RSS, the throughput has increased by 37%, and user satisfaction has increased by 56%.	High
Hou et al., 2023[60]	The RL method of PPO	PPO's overall data rate is 16% and 25% higher than that of TRPO and SSS.	High
Alshaer et al., 2023[61]	The RL method of DQN	The speed has increased by about 10% and 20%, respectively, compared to UBNS and FNS.	Low
Verma et al., 2023 [62]	RL + transfer learning	The average throughput and user satisfaction of the system have been improved.	High
Lou et al., 2024[63]	Q-learning + processing time optimization	Compared to RSS: approximately 25% reduction in handover time loss.	Low
Fonseca et al., 2024[64]	RL + trajectory prediction model	Compared with STD-LTE and Smart HO algorithms, this method has increased system throughput by 146% and 59%, respectively.	High

Table 3. Key reported metrics, application scenarios, and critical interpretations of representative ML and RL methods.

Model family	**Representative studies**	**Best-suited scenario**	**Key reported metric**	**Critical interpretation**
ANN / shallow ML	[22-27]	Low-dimensional AP selection with stable mobility and limited state variables	Accuracy values around 72.2-96.7%; selected ANN-based studies report throughput improvement and handover-frequency reduction relative to RSS or single-ANN baselines.	Performs well when inputs are compact and decision boundaries are learnable, but retraining may be required when topology, traffic, or mobility distributions shift.
DNN / CNN / proactive DL	[28-29, 31-33, 36]	Nonlinear channel, load, orientation, and spatial-interference patterns	Reported metrics include >95% handover accuracy in selected deep-learning studies, throughput gains, and reduced switching frequency.	DNNs capture nonlinear interactions, while CNN-style models are stronger when the network state has spatial structure; their main cost is higher training and data demand.
Mobility- and multipath-aware learning	[30, 33]	Mobility-aware AP selection, multipath transmission, and handover reduction	Reported benefits include reduced handover frequency, lower latency, and improved energy efficiency or throughput in selected studies.	Temporal or mobility-aware features improve handover stability, but performance depends heavily on representative movement traces and deployment geometry.
Q-learning / deep RL	[44-45, 49]	Discrete AP-selection, handover-trigger optimization, and scalable value-function approximation	Reported improvements include reduced handover frequency and higher throughput relative to RSS, FNS, or other fixed baselines.	Q-learning is simple and interpretable for small action spaces; deep RL improves scalability but can be less stable without careful reward design.
Policy-gradient / PPO	[37-38, 40]	Dynamic multi-objective optimization of throughput, satisfaction, load balance, and handover cost	Reported metrics include throughput and user-satisfaction gains; PPO reports higher overall data rate than TRPO and SSS in the reviewed study.	Policy-gradient methods suit complex control problems, but training overhead and reward sensitivity remain deployment barriers.

Multi-agent / hybrid RL	[39, 42-44]	Dense AP coordination, transfer learning, trajectory assistance, and vertical handoff optimization	One multi-agent RL study reports 37% throughput improvement and 56% user-satisfaction improvement over RSS.	Distributed learning improves coordination in dense networks, but communication overhead and convergence stability need further validation.
Recent user-centric / MPTCP / GNN methods	[15, 34-35, 65-66]	User-centric resource allocation, heterogeneous load balancing, service differentiation, and energy management	Recent studies broaden evaluation toward resource allocation, throughput-handover trade-offs, graph-based load balancing, and service/energy objectives.	These works move the field beyond single-metric throughput optimization, but cross-paper comparison remains difficult without standardized scenarios.
AI-assisted 5G/6G handover	[48]	Ultra-dense cellular and future 6G-oriented handover management	Focuses on AI-driven handover and load-balancing optimization in ultra-dense networks.	Useful for positioning LiFi/WiFi research within 6G network intelligence, although direct LiFi/WiFi benchmarking is still limited.

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