Deep Reinforcement Learning-Based Association Control Scheme for Dense WLAN Systems

Sanghui Lee, Hyeongjun Jeon
Department of Intelligent Robot Engineering
Pukyong National University
Busan, Korea
{dltkdgml4730, jun04292569}@pukyong.ac.kr

Daehyeon Nam, Jaewook Lee
Department of Information and Communication Engineering
Pukyong National University
Busan, Korea
namdh01@pukyong.ac.kr, jlee0315@pknu.ac.kr

***Abstract*—In this paper, we propose deep reinforcement learning-based association control (Deep-AC) scheme for dense WLAN system where coverage between Access Points (APs) overlaps (e.g., an indoor event hall). Deep-AC determines the association policy between users and APs to improve the fairness of overall user device data rates by preventing user congestion at specific APs and minimizing connection interruptions caused by AP switching. Evaluation results demonstrate that Deep-AC improves the fairness of overall user device data rates by up to 55.8% compared to the random association approach.**

***Index Terms*—WLAN, Deep Q-Network, Reinforcement Learning, Association control, Jain's fairness index**

I. Introduction

With the rapid development of the information era, WLAN has been established via WiFi Access Points (APs) in various locations to enable internet services anywhere. [1] Today, wireless connectivity plays a crucial role not only in traditional web access but also in supporting diverse applications such as IoT services, real-time video streaming, online gaming and smart city infrastructures. In such contexts, ensuring reliable and fair resource allocation among a large number of devices has become a crucial challenge. [2]

However, WLANs constructed by APs are managed independently, resulting in limitations in coverage expansion and network management difficulties, especially in dense AP environments. [3] In high-density scenarios such as airports, campuses, or indoor event halls, overlapping AP coverage can cause significant interference and unbalanced associations. Many users tend to connect to only a specific AP, even when multiple alternatives exist nearby. This not only leads to user congestion and degraded internet performance but also contributes to problems such as service interruption during AP switching, latency increase, and reduced Quality of Service (QoS). [4]

Recently, Mesh WiFi technology [5], which distributes multiple APs to extend coverage, has been actively studied and commercialized. Nevertheless, existing Mesh WiFi techniques are inefficient in densely populated areas, such as indoor event halls with overlapping AP coverage. [6] Consequently, many users are connected to only a specific AP among APs distributed in similar locations, leading to network congestion and resulting in degraded internet performance. Furthermore, Mesh WiFi systems support only specific versions or products from the same vendor. Therefore, operators must replace their existing WiFi AP infrastructure. This results in considerable financial pressure, particularly for small-scale operators.

To overcome these limitations, a variety of approaches have been actively explored in dense WLANs. [7], [8] We propose a deep reinforcement learning-based association control (Deep-AC) scheme that determines optimal device-AP association policies without modifying the existing infrastructure. The Deep Q-Network (DQN) algorithm [9] is applied to the association policy. Experimental results show that the proposed method effectively selects APs that significantly satisfy the required data rate for each device.

The remainder of this paper is organized as follows. The system architecture and association control scheme are described and developed in Section II. Then, the simulation results are given in Section III, and followed by the concluding remarks in Section IV.

II. Intelligent Cluster WLAN System

A. System Architecture

Figure 1 shows the proposed system architecture, consisting of a network controller, M WiFi APs, and N user devices. The WiFi APs maintain their original function of providing internet access without modification, eliminating the need for infrastructure changes.

The network controller collects messages transmitted by each device, which contain data such as current communication status and the connected AP. The specific contents of these messages may change depending on the purpose of implementation. These messages are used to apply the Deep-AC scheme to determine the optimal AP for each device. Then the network controller informs devices of the determined APs.

Upon receiving the message, the device changes its connection to the newly assigned AP by the network controller. Then, the device stores the data usage and information about the currently connected AP (e.g., MAC address or SSID), and then transmits this information to the network controller. This entire process is designed to repeat periodically.

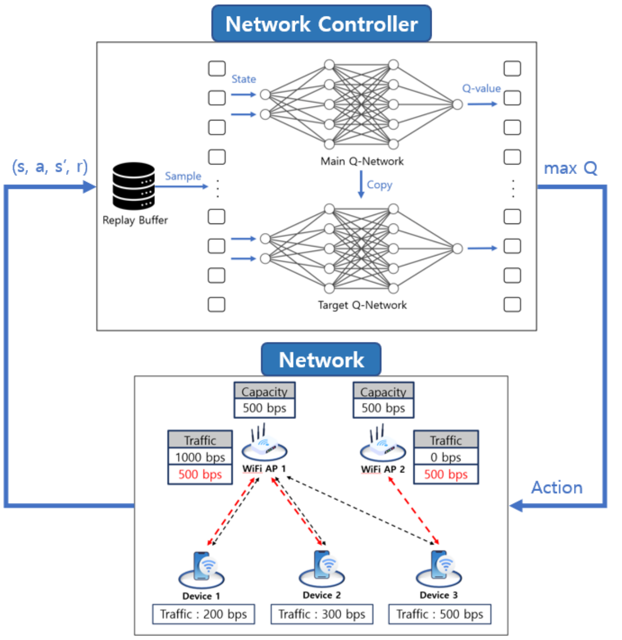


Fig. 1. System Architecture.

B. Deep Reinforcement Learning-based Association Control Scheme

In this study, the network controller learns to select optimal APs for each device using the DQN algorithm [9], as shown in Figure 1. To obtain the optimal AP association policy, the DQN algorithm is defined with state space (S), action space (A), and reward (R).

The state space is defined as

$$S = \prod_{n=1}^{N} W_n \times \prod_{n=1}^{N} D_n \tag{1}$$

where W_n={1,2,. . . ,M} represents the AP to which device n is currently connected, and D_n={0,. . . ,D_{max}} represents the data rate demand of device n.

The action space is defined as

$$A = \prod_{n=1}^{N} A_n \tag{2}$$

where $A_n = W_n$ denotes the AP to which the device n should be connected.

To emphasize fairness in terms of demand satisfaction among devices, the reward is defined using Jain's fairness index [10] as follows:

$$r(s,a) = \frac{\left[\sum_{m=1}^{M} \theta_m \left(r_n(s,a)\right)\right]^2}{M \sum_{m=1}^{M} \left[\theta_m \left(r_n(s,a)\right)\right]^2} \tag{3}$$

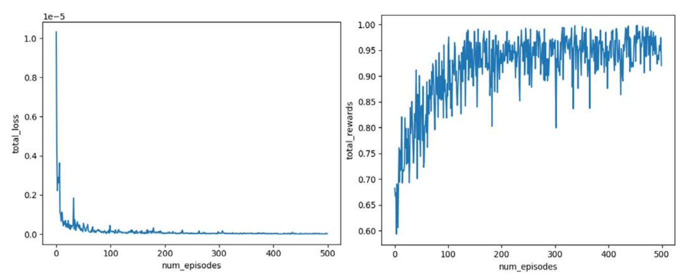
where the function θ_m represents the sum of $r_n(s,a)$ values for all devices connected to AP m. $r_n(s,a)$ denotes the degree of demand satisfaction of device n, indicating that smaller values represent better demand satisfaction, and it is defined as

$$\begin{aligned} r_n(s,a) = \max \Bigg\{ & d_n - \frac{B_{a_n}}{N_{a_n}} \Big(\delta(w_n = a_n) \\ & + p(1 - \delta(w_n = a_n)) \Big),\ 0 \Bigg\} \end{aligned} \tag{4}$$

In this equation, d_n is the data rate required by device n, B_{a_n} is the data rate provided by the selected AP a_n, and N_{a_n} is the number of devices connected to that AP. The function δ returns 1 if the AP remains unchanged, and 0 otherwise. The variable p represents the ratio of service time excluding disconnection due to AP switching. Consequently, the reward $r(s,a)$ ranges from 0 to 1, with values closer to 1 representing higher levels of fairness.

Based on this formulation, the network controller utilizes techniques such as ϵ-greedy, replay buffer, and target networks to learn the optimal AP association policy.

III. Simulation Results



(a) Loss (b) Reward

Fig. 2. Performance graph of loss and reward.

The network controller was trained over 500 episodes, each with 20 steps. The simulation environment consisted of 3 APs and 6 devices, each with different data rate demands.

During training, as shown in Figure 2, the average loss per episode initially exhibited high values but rapidly decreased and stabilized, while the average reward gradually increased. These results demonstrate that the network controller effectively learned optimal policies over time.

As shown in Figure 3, the fairness of resource allocation was measured for each method to evaluate how effectively each method allocates resources. The Random method connects devices to APs randomly, and the Static method assigns an equal number of devices to each AP without considering individual demands. As a result, these methods do not achieve a high level of fairness in resource allocation, especially in environments with diverse device demands. In contrast, the proposed Deep-AC method significantly outperformed other methods, demonstrating effective AP selection and fair resource allocation.

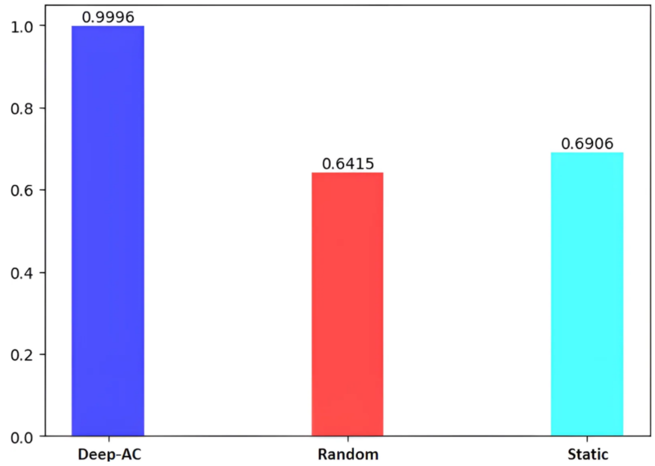


Fig. 3. Performance comparison.

IV. Conclusion

In this paper, we proposed a Deep-AC scheme to determine the optimal device-AP association policy in dense wireless environments. The proposed method enables efficient AP association without requiring modifications to existing WiFi AP infrastructure, which helps reduce deployment costs. Simulation results demonstrated that the proposed system not only satisfies the data rate requirements of devices but also improves fairness in resource allocation.

In future work, we plan to extend this approach by incorporating dynamic user mobility and real-time network conditions to further enhance adaptability and performance.

Acknowledgment

This work has been supported in part by National Research Foundation (NRF) of Korea Grant funded by the Korean Government (MSIT) (No.RS-2025-00558169) and in part by Institute of Information & communications Technology Planning & Evaluation (IITP) grant funded by the Korea government(MSIT) (No. RS-2023-00225468)

References

[1] S. Szott, K. Kosek-Szott, P. Gawłowicz, J. T. Gómez, B. Bellalta, A. Zubow, and F. Dressler, "Wi-Fi Meets ML: A Survey on Improving IEEE 802.11 Performance With Machine Learning," IEEE Comms Surveys & Tutorials., vol. 24, no. 3, pp.1843–1893, June 2022.

[2] E. Mozaffariahrar, F. Theoleyre, and M. Menth, "A survey of Wi-Fi 6: Technologies, advances, and challenges," Future Internet., vol. 14, no. 10, pp.293, October 2022.

[3] S. Bayhan, E. Coronado, R. Riggio, and A. Zubow, "User-AP Association Management in Software-Defined WLANs," IEEE Transactions on Network and Service Management., vol. 17, no. 3, pp.1838–1852, June 2020.

[4] H. D. Balbi, D. Passos, R. C. Carrano, L. C. S. Magalhães, and C. V. N. Albuquerque, "Association stability and handoff latency tradeoff in dense IEEE 802.11 networks: A case study," Computer Communications., vol. 159, pp.175–185, June 2020.

[5] I. F. Akyildiz, X. Wang, and W. Wang, "Wireless mesh networks: a survey," Computer networks, vol. 47, no. 4, pp. 445–487, March 2005.

[6] M. Rethfeldt, T. Brockmann, B. Beichler, C. Haubelt, and D. Timmermann, "Adaptive multi-channel clustering in ieee 802.11 s wireless mesh networks," Sensors., vol. 21, no. 21, pp.7215, October 2021.

[7] W. Wu, Y. Liu, J. Yao, X. Fang, F. Shan, M. Yang, Z. Ling, and J. Luo, "Learning-aided client association control for high-density WLANs," Computer networks., vol. 212, pp.109043, July 2022.

[8] A. Chadda, M. Stojanova, T. Begin, A. Busson, and I. G. Lassous, "Assigning channels in WLANs with channel bonding: A fair and robust strategy," Computer networks., vol. 196, pp.108200, September 2021.

[9] V. Mnih, K. Kavukcuoglu, D. Silver, A. Graves, I. Antonoglou, D. Wierstra, and M. Riedmiller, "Playing Atari with Deep Reinforcement Learning," arXiv preprint arXiv:1312.5602, December 2013.

[10] A. B. Sediq, R. H. Gohary, R. Schoenen, and H. Yanikomeroglu, "Optimal tradeoff between sum-rate efficiency and Jain's fairness index in resource allocation," IEEE Trans. Wireless Commun., vol. 12, no. 7, pp. 3496–3509, July 2013.