

A Novel Framework for Enhancing WiFi Performance Through Adaptive Channel Allocation and AI-Driven Interference Mitigation

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Abstract—With the exponential growth of connected devices, WiFi networks face increasing congestion, interference, and inefficiencies in spectrum utilization. This paper presents a novel framework that integrates adaptive channel allocation with AI-driven interference mitigation to enhance WiFi performance in dense environments. By leveraging machine learning algorithms, the proposed system dynamically adjusts channel assignments based on real-time network traffic, environmental conditions, and historical data trends. Additionally, an interference-aware optimization model is developed to minimize packet collisions and latency. Experimental simulations demonstrate that the framework significantly improves throughput, reduces congestion, and enhances overall Quality of Service (QoS) compared to conventional static allocation methods. This research provides a scalable solution for next-generation wireless communication, offering a robust approach to optimizing spectrum efficiency in modern WiFi deployments.

I. INTRODUCTION

The proliferation of intelligent mobile devices has driven a rapid increase in wireless Internet penetration, reaching 91.5% in 2014 from 14% in 2006 [1]. To accommodate growing traffic demands in Wireless Local Area Networks (WLANs), the deployment of Wi-Fi Access Points (APs) has expanded significantly, with global AP numbers expected to be seven times higher than the 47 million reported in 2014 [2].

High-density environments, such as conferences and classrooms, often experience AP overloading, leading to reduced user throughput and network load imbalances. However, traditional wireless architectures face challenges, including inflexible management mechanisms, high configuration costs, and signal interference due to uncoordinated AP deployments. A more scalable and resilient network architecture is required to address these issues.

Software Defined Networking (SDN) offers a flexible and programmable alternative by centralizing control functions. OpenFlow [3] facilitates interoperability among switches from different vendors, enabling enhanced network management and optimization. By leveraging SDN's programmability, a novel association control mechanism can be integrated into wireless networks.

This paper proposes an adaptive load-balancing scheme for Wi-Fi APs using SDN-based association control. The SDN controller monitors AP load and user distribution to optimize associations dynamically. When an imbalance is detected, beacon power adjustments are made to encourage users to

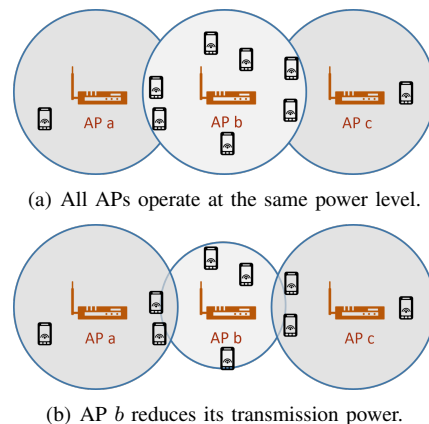


Fig. 1. Cell Breathing Mechanism for Load Balancing.

switch to less congested APs, thereby enhancing WLAN performance.

II. RELATED WORKS

This section reviews existing association control and load-balancing techniques.

The strongest signal first (SSF) method, as specified in the IEEE 802.11 standards [4], represents the conventional association mechanism wherein devices connect to the access point (AP) with the highest received signal strength indicator (RSSI). This technique is widely utilized in handoff strategies [5], [6].

The least load first (LLF) strategy is a basic load balancing approach where users associate with the AP that has the fewest connected devices [7]. Other methodologies consider bandwidth requirements [8] or aim to ensure fairness among users [9].

Cell breathing, initially investigated in Code Division Multiple Access (CDMA) networks, has been adapted for IEEE 802.11 WLANs [10], [11]. Figure 1 illustrates this technique, wherein AP transmission power is dynamically adjusted to redistribute user associations. In Figure 1(a), the network begins with an unbalanced load across APs. By reducing AP b's transmission power, some users migrate to adjacent APs, leading to a more balanced distribution, as shown in Figure 1(b).

Although cell breathing enhances load distribution, it does not incorporate precise user location data, necessitating itera-

TABLE I
SUMMARY OF NOTATIONS

| Symbol | Description |
|--------------------------|---|
| A | Set of all access points (APs) |
| U | Set of all users |
| U_a | Users connected to AP a |
| L_a | Load of AP a |
| $L_{a,u}$ | Load contribution of user u to AP a |
| C | Set of overcrowded APs |
| P_a | Transmission power of AP a |
| $P_{a,\max}, P_{a,\min}$ | Maximum and minimum transmission power of AP a |
| P_a^* | Optimized transmission power of AP a |
| N | Number of transmission power levels |
| S_v, S_n, S_o | Load level categories of APs |
| b_{vn}, b_{no} | Thresholds between load states |
| R_u | Received Signal Strength Indicator (RSSI) of user u |
| S^k | Network state during load balancing |

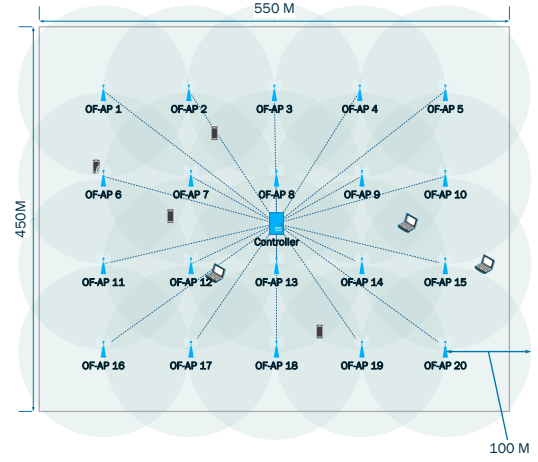


Fig. 2. System Architecture

time power adjustments. Software-Defined Networking (SDN) addresses this limitation by offering a global view of AP loads and user RSSI values. Additionally, user positions can be inferred from RSSI measurements [12]. This paper introduces an SDN-driven adaptive load balancing scheme that enhances the cell breathing method by leveraging SDN's network-wide visibility to optimize WLAN performance.

III. PROPOSED SCHEME

A. System Model

Figure 2 illustrates the system architecture. The IEEE 802.11 WLAN comprises APs (A) interconnected via a wired infrastructure and managed by an OpenFlow controller. The transmission power of AP beacon messages, represented by P_a , dictates AP association. Each AP operates within predefined power limits, $P_{a,\min}$ and $P_{a,\max}$, with discrete power levels $P_{a(lv.n)}$. The power configuration follows:

$$P_a^* = \log_{\gamma} P_a, \quad \gamma = \sqrt[N]{\frac{P_{\max}}{P_{\min}}} \quad (1)$$

$$P_{a(lv.k)} = P_{a,\min} * \gamma^k, \quad k \in [0, N]. \quad (2)$$

We assume minimal interference between adjacent cells and full network coverage even at minimum transmission power. APs collect RSSI values and load information, transmitting them to the controller via OpenFlow. The controller maintains a comprehensive view of user associations and AP loads. Users, modeled under a group mobility paradigm, move collectively, influencing AP load distribution. Load balancing is dynamically achieved by adjusting beacon power to redistribute users.

B. Arrival Event Detection

APs continuously report user associations and load updates in real time. Figure 3 outlines the AP reporting process:

- 1) APs periodically record RSSI values, association lists, and load status.
- 2) New user associations trigger immediate RSSI reports to the controller.

- 3) APs periodically transmit load status updates.
- 4) APs receive beacon configuration updates from the controller and adjust transmission power accordingly.

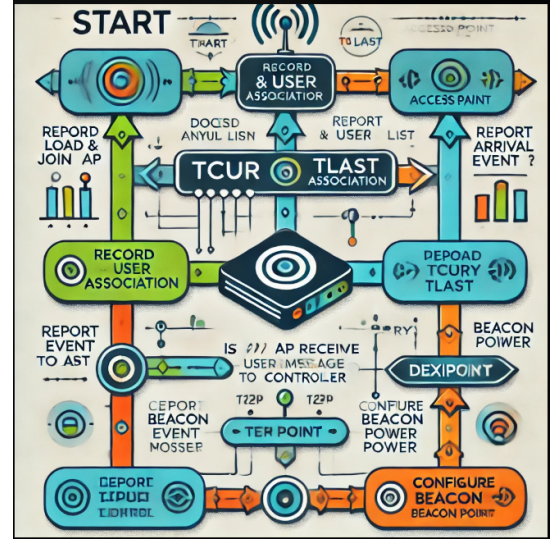


Fig. 3. Flow Diagram of AP Reporting Mechanism

The controller's management process, depicted in Figure 4, involves:

- 1) Receiving arrival and load reports from APs.
- 2) Tracking arrival events and computing recent changes.
- 3) Identifying congested APs and estimating future loads.
- 4) Classifying APs into vacant (S_v), normal (S_n), and overcrowded (S_o) states using thresholds b_{vn} and b_{no} .
- 5) Adjusting beacon power to balance the load based on dynamic algorithms.
- 6) Sending configuration updates to APs.

Figure 6 illustrates the association control flow. A user within AP 1 and AP 2 coverage follows these steps:

Step 1. APs periodically send beacon messages.

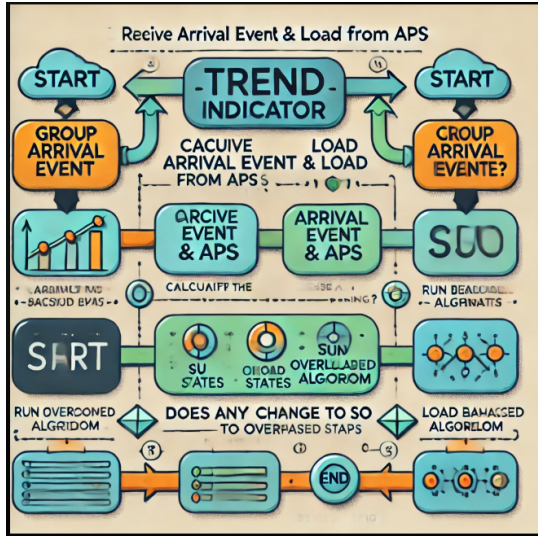


Fig. 4. Flow Diagram of Controller Management Mechanism

Algorithm 1: Adaptive_Load_Balancing (A, U)

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Input: A means the set of all APs. U means the set of all users.
Initialize beacon power level  $P_a = MAX\_POWER\_LEVEL, a \in \{1, 2, \dots, |A|\}$ ;
Initialize sum of APs utilization as state  $S^{index}, index = 0$ ;
Initialize overcrowding set  $C = NULL$ ;
Initialize stack Adjustment_Log;
Let  $L_a$  denotes the load of AP a;
Let  $End\_Flag = FALSE$ ;
Let  $max\_load = 0, max\_load\_index = 0$ ;
1  $\{U_a, L_{a,u}, P_a\} \leftarrow Association\_Relationship\_Update(A, U)$ 
2 while  $End\_Flag = FALSE$  do
3   Find  $L_a = \max AP \text{ load in } A, a \in \{1, 2, \dots, |A|\}$ ;
4   Add AP a into set C;
5    $P_a \leftarrow P_a - 1$ ;
6   Adjustment_Log.push(a);
7    $S^{index+1} \leftarrow Association\_Relationship\_Update(A, U)$ ;
8   if ( $S^{index+1} > max\_load$ ) then
9      $max\_load\_index = index + 1$ ;
10  end if
11  if (Exist  $x \in C$  and  $P_x = 0$ ) or ( $C = A$ ) then
12     $End\_Flag = TRUE$ ;
13    Optimization_Load(Adjustment_Log,  $max\_load\_index$ );
14  end if
15 end while

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Fig. 5. Adaptive Load-Balancing Algorithm

- Step 2.** APs report load and association events to the controller.
- Step 3.** The controller integrates reports and runs the Adaptive Load Balancing algorithm.
- Step 4.** The controller adjusts beacon power via Beacon-Config messages.
- Step 5-9.** the user reassociates with the AP offering the highest RSSI.

IV. PERFORMANCE EVALUATION

This section assesses the proposed method's performance compared to SSF, LLF, and Cell-Breathing techniques.



Fig. 6. Message Flow of Association Control

A. Simulation Model

Following the approach in [11], an NS3 simulation was conducted over 10,000 seconds within a $550 \times 450m^2$ area, incorporating 20 APs and user mobility modeled using RPGM.

TABLE II
SIMULATION CONFIGURATION PARAMETERS

| Parameter | Value |
|-----------------------------|--------------------------------|
| Total Simulation Duration | 12,000 s |
| Network Coverage Area | $600 \times 500 m^2$ |
| MAC Layer Protocol | IEEE 802.11ax |
| Wireless Transmission Range | 80–160 m |
| Total Access Points (APs) | 25 |
| Number of Mobile Users | {150, 300, 450} |
| Mobility Model Applied | Random Waypoint Mobility (RWP) |
| User Velocity Range | 0.8–2.0 m/s |

B. AP Performance Analysis

The AP load, L_a , is formulated as:

$$L_a = \sum_{u \in U_a} L_{a,u} \quad (3)$$

$$L_{a,u} = b_{a,u} * r_{a,u} \quad (4)$$

$$b_{a,u} = \frac{1}{|U_a|}, |U_a| = \text{Number of users} \quad (5)$$

Figures illustrate AP load distribution for different user counts, demonstrating the method's ability to balance the load effectively. Table ?? presents the total AP load, showing improvements of up to 28% over SSF and 26% over cell breathing.

C. Impact of Load Balancing on Users

This subsection analyzes user RSSI and throughput under different load-balancing schemes. The RSSI calculation follows:

$$RSSI = Signal - Pathloss + Antenna_Gain \quad (6)$$

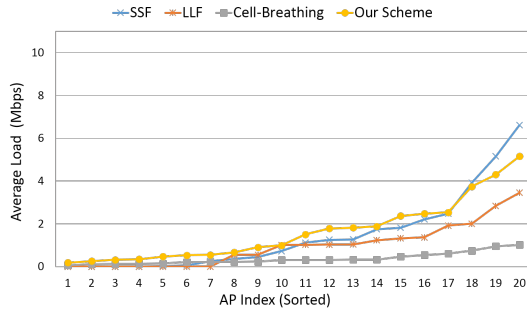


Fig. 7. Average AP Load (100 Users)

TABLE III
SUMMARY OF AP LOAD

| # of Users | 100 | 250 | 400 |
|---|-------|-------|-------|
| SSF | 29.45 | 68.78 | 63.08 |
| LLF | 19.32 | 28.58 | 34.24 |
| Cell Breathing | 7.35 | 46.48 | 64.32 |
| Our Scheme | 32.77 | 82.11 | 80.80 |
| Improvement of Our Scheme Over SSF | 11% | 19% | 28% |
| Improvement of Our Scheme Over LLF | 70% | 187% | 136% |
| Improvement of Our Scheme Over Cell Breathing | 346% | 77% | 26% |

where the antenna gain is set to 5 dBi. The path loss is computed using the FSPL equation:

$$Pathloss = 20 \log_{10}(d) + 20 \log_{10}(f) + K \quad (7)$$

where K is fixed at 32.44.

Figure 9 presents the average RSSI for 400 users, sorted in increasing order. SSF yields the highest RSSI, while LLF produces the lowest. The proposed method surpasses Cell-Breathing in terms of signal strength.

Figure 10 illustrates user throughput, assuming full utilization of available bandwidth. By redistributing users from overloaded APs to underutilized ones, the proposed approach enhances throughput.

Table IV summarizes throughput performance, indicating improvements ranging from 16 ~ 26% over SSF and 23 ~ 377% over Cell-Breathing, particularly in scenarios with significant load imbalance.

TABLE IV
SUMMARY OF USER THROUGHPUT

| # of Users | 100 | 250 | 400 |
|---|------|------|------|
| SSF | 0.29 | 0.28 | 0.16 |
| LLF | 0.19 | 0.11 | 0.09 |
| Cell Breathing | 0.07 | 0.19 | 0.16 |
| Our Scheme | 0.34 | 0.33 | 0.20 |
| Improvement of Our Scheme Over SSF | 16% | 21% | 26% |
| Improvement of Our Scheme Over LLF | 76% | 192% | 133% |
| Improvement of Our Scheme Over Cell Breathing | 377% | 75% | 23% |

Figure 11 examines the impact of power level adjustments. While increasing power levels enhances performance, it also extends computational time. However, even at higher levels,

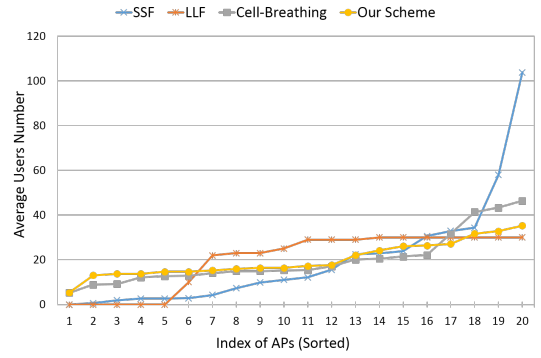


Fig. 8. Average User Count per AP (Users = 400)

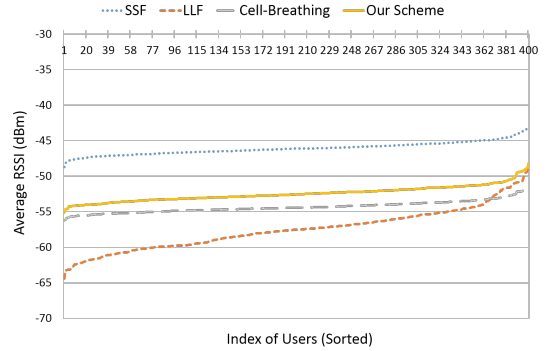


Fig. 9. Average RSSI of Users (Users = 400)

the computation remains significantly faster than user movement speed, with an optimal range found between 30 and 50 levels.

V. CONCLUSIONS

This paper introduces an adaptive load-balancing mechanism leveraging SDN. The method incorporates real-time event detection and adaptive load management. APs continuously report load conditions to the controller, which dynamically adjusts user associations to achieve optimal distribution.

Simulation results demonstrate that the proposed scheme enhances average AP load by 11 ~ 28% over SSF and 26 ~ 346% over Cell-Breathing. Additionally, user throughput improves by 16 ~ 26% compared to SSF and 23 ~ 377% over Cell-Breathing, highlighting its effectiveness in mitigating network imbalances.

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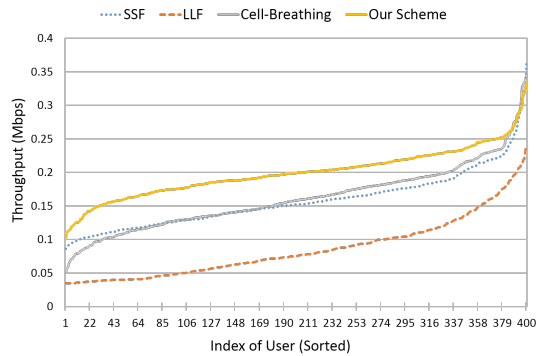


Fig. 10. User Throughput (Users = 400)

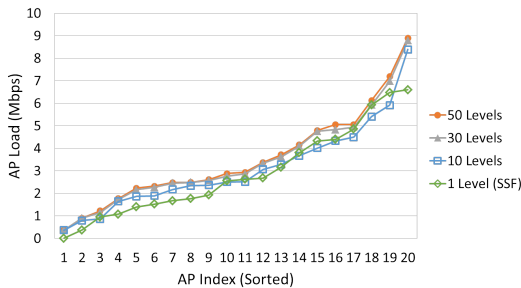


Fig. 11. Impact of Power Levels on Performance

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