Machine Learning-Based Joint TX Power and RX Sensitivity Control for Overlapping Basic Service Set Interference Mitigation in Dense Internet of Things Wireless Networks

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Abstract— **The recent increase in Internet of Things devices and wireless network equipment has led to frequent occurrences of overlapping basic service set environments, where multiple wireless networks share the same or adjacent channels within the same space. In these environments, network quality degrades owing to channel interference. Previous studies have attempted to avoid interference by blocking some links or using time-division methods; however, these methods have limitations in responding to real-time environmental changes and improving overall network throughput and spatial reuse rates. This study proposes a Machine Learning-based joint control technique for TX power and RX sensitivity. This technique is implemented in both centralized and distributed architectures. Each node recognizes the network state, predicts optimal parameters through a Machine Learning model, and applies them to minimize interference. Experimental results demonstrate that the proposed technique achieves up to 47.1% higher effective throughput and 29.6% better measured Signal-to-Interference-plus-Noise-Ratio compared with the conventional technique. The proposed distributed technique demonstrated approximately 46.4% higher effective throughput (21.43 Mbps) than the conventional central technique under low traffic load and maintained relatively high link quality even in environments with increased traffic load. While the proposed distributed method incurred higher control overhead owing to increased computational requirements compared with the conventional distributed method, the distributed architecture enables each Access Point to operate independently, allowing for parallel processing benefits in actual network deployments.**

Keywords- Overlapping Basic Service Set; Machine Learning; TX power and RX sensitivity Control; Internet of Things Wireless Networks.

I. INTRODUCTION

The recent rapid growth of Internet of Things (IoT) devices and wireless network equipment has led to the frequent occurrence of Overlapping Basic Service Set (OBSS) environments, where multiple wireless networks share the same or adjacent channels within the same space [1]. In these environments, the performance degradation due to channel interference increases significantly. Furthermore, attackers can intentionally generate interference signals or unnecessary traffic, resulting in jamming attacks that threaten the network availability and reliability [2]. Existing OBSS interference mitigation techniques primarily avoid interference issues by blocking certain links or applying time-division methods. However, these approaches have limitations: they degrade the overall network throughput and Spatial Reuse (SR) rates [3]. They often focus solely on TX power control (on sender side) or rely on predefined probability models, thereby failing to respond effectively to real-time changes in the network environment or dynamic traffic patterns. Furthermore, they do not consider controlling the RX sensitivity (on receiver side), which can also affect the interference. Therefore, this study views the OBSS environment as a resource to be managed efficiently, and not merely as a constraint to avoid. This study proposes a Machine Learning (ML)-based framework that jointly controls TX power and RX sensitivity. This study implemented and compared the performances of centralized and distributed architectures. The centralized approach utilizes network-wide information to enable global optimization, whereas the distributed approach allows each Access Point (AP) to perform predictions independently based solely on local information, ensuring scalability and practicality. We compared and analyzed the performance of the conventional technique and two proposed approaches. The main contributions of this study are as follows:

- Centralized and distributed ML architectures are proposed, demonstrating the trade-off between performance and control overhead in OBSS networks.
- TX power and RX sensitivity are optimized to support simultaneous connections for more devices.
- The trade-off between the Signal-to-Interference-plus-Noise-Ratio (SINR) of AP–Station (STA) communication pairs and the overall network connectivity is analyzed, and criteria for simultaneous connections are presented.

The structure of this paper is as follows: Section II reviews the research related to OBSS interference mitigation and ML-based network optimization. Section III describes the proposed technique, and Section IV presents the simulation model. Section V details the experimental environment and Section VI discusses the performance evaluation results. Finally, Section VII presents conclusions and directions for future research.

II. RELATED WORK

Jung et al. [4] proposed an OBSS packet detection SR technique based on an optimized TX power control to achieve high throughput in OBSS environments. The proposed technique derives the optimal TX power that maximizes the communication success probability through probabilistic geometric analysis and adjusts the clear channel assessment threshold accordingly to reduce interference and increase channel access opportunities. However, this technique has limitations in that it calculates the optimal values based on predefined probability models, making it difficult to adapt flexibly to real-time changes in the network environment or dynamic traffic patterns. Zhu et al. [5] improved the performance of coordinated SR (CSR) in an IEEE 802.11be environment through TX power adjustment and distributed optimization using adaptive CSR and distributed CSR. However, this study did not address RX sensitivity control or adaptability to real-time environmental changes via ML, thereby limiting the comprehensive optimization of the transmit/receive parameters in dynamic traffic environments. In addition, Haxhibeqiri et al. [6] proposed a centralized CSR approach to centrally optimize transmit parameters to resolve OBSS interference issues and enhance network throughput. This approach aims to optimize TX power and Modulation and Coding Scheme (MCS) index to avoid interference at the main receiver. However, centralized structures have limited SR efficiency in dynamic environments owing to structural constraints, such as scalability, overhead, and single points of failure. It also has the limitation of focusing solely on TX power without simultaneously considering RX sensitivity joint control. Wojnar et al. [7] proposed a learning-based scheduling technique using multi-armed bandits (MABs) to optimize the TX power of multiple APs in an IEEE 802.11bn CSR environment. Specifically, they contributed to an 80% throughput improvement using hierarchical MAB (H-MAB) in a centralized manner. However, this study has limitations in terms of interference management, because it does not consider RX sensitivity control.

Previous studies have proposed various approaches to mitigate interference and enhance the SR efficiency in OBSS environments, such as TX power optimization and centralized or distributed parameter control. However, most of these approaches rely on predefined models, making them difficult to adapt flexibly to real-time changes in network environments and dynamic traffic patterns. Furthermore, comprehensive control strategies that simultaneously consider both TX power and RX sensitivity are still lacking, and fail to actively incorporate these dynamic factors through ML-based predictions.

III. OBSS INTERFERENCE MANAGEMENT VIA ML-BASED JOINT TX POWER AND RX SENSITIVITY CONTROL

The proposed technique is illustrated in Figure 1. The left figure shows the problem of reduced overall network throughput due to OBSS interference when each AP and STA shares the same or adjacent channels in the existing OBSS environment. In contrast, the figure on the right shows the results of applying the proposed distributed control method. Each node dynamically adjusts its TX power and RX sensitivity through ML-based prediction, thereby minimizing interference and improving the overall network throughput. In the case of the proposed centralized control method, a single AP controls all STAs and APs to minimize interference.

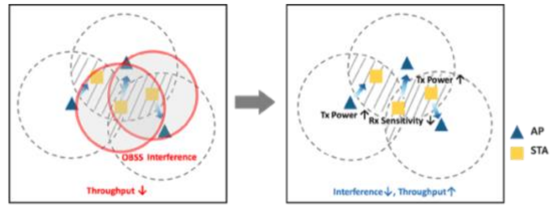

Figure 1. Distributed control for OBSS interference mitigation.

Figure 2 illustrates the overall operational flow of the TX power and RX sensitivity joint control framework proposed in this study.

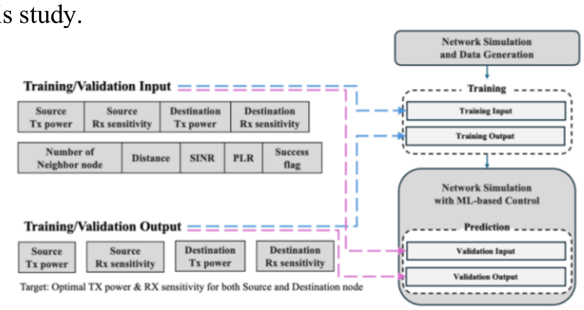

Figure 2. Overall flow for TX power and RX sensitivity control using ML.

First, simulations were repeatedly performed under various OBSS environments and network configurations to collect network environment data. This includes the transmit/receive parameters of each node, number of neighboring nodes, distance, SINR, Packet Loss Rate (PLR), and communication success. Subsequently, the ML model was trained on the collected dataset to predict the optimal TX power and RX sensitivity for each communication pair (source–destination). Detailed information regarding the real-time network environment is summarized in Table 1.

TABLE I. NETWORK ENVIRONMENT INFORMATION

Type	Description	Scope
Source ID	Transmitting node	1–45
Destination ID	Receiving node	1–45
Source TX power	Transmitting node's TX power	15–23 dBm
Source RX sensitivity	Transmitting node's RX sensitivity	-90–-75 dBm
Destination TX power	Receiving node's TX power	15–23 dBm
Destination RX sensitivity	Receiving node's RX sensitivity	-90 – -75 dBm
Number of neighbors	Number of nodes within 50 m of the transmitting node	0–44
Distance	Distance between transmitter and receiver nodes	0–141.4 m
SINR	Estimated SINR at the receiving node	-10 – 40 dB
PLR	Packet loss rate	0–1
Success flag	Success of communication connection	0 or 1

The source ID is the identifier of the transmitting node (AP or STA). The destination ID is the identifier of the receiving node. Source TX power and source RX sensitivity are the transmitting node's current TX power (range 15–23 dBm) and RX sensitivity (-90 – -75 dBm), respectively. Destination TX power and destination RX sensitivity refer to the TX power of the receiving node and the RX sensitivity, respectively. The number of neighbors is the number of surrounding nodes within 50 m of the transmitting node. Distance is the physical distance (m) between the transmitting and receiving nodes, which directly affects path loss. The SINR is the current SINR of the receiving node (dB), indicating the instantaneous link quality. Approximately -10 to 40 dB is an estimated value calculated during training data generation. PLR denotes the packet loss rate. The success flag indicates whether the communication connection was successful, represented by 0 or 1, and serves as the training label for supervised learning.

IV. SIMULATION MODEL

This section presents the simulation model considered in this study. It includes the high-density IEEE 802.11ax network configuration, the wireless channel assumptions, and the formulations of key variables such as TX power, RX sensitivity, and SINR. Figure 3 shows the network configuration used in the simulation.

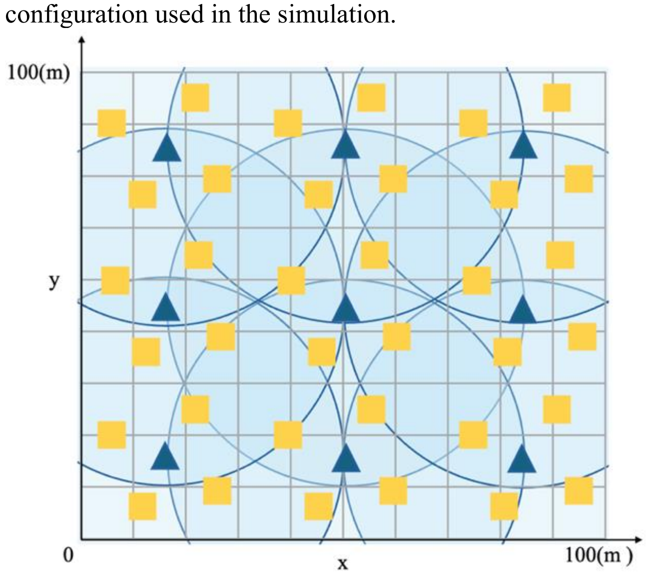

Figure 3. Network configuration.

This study assumes a high-density IEEE 802.11ax wireless network environment deployed within a 100 m × 100 m square area, operating only on a single 20 MHz channel in the 2.4 GHz band [8]. The network comprises nine APs arranged in a 3 × 3 grid pattern at 33.33 m intervals, with four STAs assigned per AP, randomly distributed across each area. This configuration creates an OBSS environment where multiple BSSs operate on the same channel, causing co-channel interference. The 33.33 m spacing between APs was specifically chosen to represent high-density deployment scenarios commonly assumed in smart building and industrial WLAN studies, where coverage overlap is unavoidable. This symmetric arrangement ensures that interference patterns are equally distributed from all directions, providing an unbiased testing environment for evaluating the proposed joint control algorithm's performance under realistic interference conditions.

The wireless channel is modeled using a log-distance path loss model that includes shadow fading, as shown in (1) [9][10].

$$PL(d) = PL_0 + 10\alpha log_{10}\left(\frac{d}{d_0}\right) + X_\sigma \tag{1}$$

Here, $PL_0 = 46.7dB$ is the path loss at the reference distance $d_0 = 1\ m$, and $\alpha = 3.5$ is the path loss exponent for indoor environments. d denotes the distance (m) between the transmitter and receiver, and $X_\sigma \sim N(0, \sigma^2)$ is the shadow fading component with $\sigma = 4dB$.
The noise power is calculated as in (2).

$$\begin{aligned} N &= N_0 + 10\log_{10}(BW) + NF \\ &= -174 + 10\log_{10}(20 \times 10^6) + 7 \\ &= -94\ dBm \end{aligned} \tag{2}$$

Here, $N_0 = -174\ dBm/Hz$ is the thermal noise power density at 290 K, $BW = 20\ MHz$ is the channel bandwidth, and $NF = 7\ dB$ is the receiver noise figure.

The SINR is a key indicator of link quality and achievable data transmission rates in wireless networks [11]. For each communication link, both the downlink and uplink SINR values are calculated. The SINR for the downlink transmission from AP_j to STA_i is calculated as shown in (3).

$$SINR_{DL(i,j)} = \frac{P_{rx(i,j)}}{N_i + I_i} \tag{3}$$

Here, $P_{rx(i,j)} = P_{tx(j)} - PL(i,j)$ represents the received signal power, where $P_{tx(j)}$ denotes the TX power of AP_j, and $PL(i,j)$ denotes the path loss between AP_j and STA_i. N_i is the noise power at STA_i, calculated as $N_i = kTB \cdot NF$, where k is the Boltzmann constant, T denotes the temperature, B denotes the bandwidth (20 MHz), and NF denotes the noise figure (7 dB). I_i is the interference from the other APs and active STAs, as shown in (4).

$$I_i = \sum_{k \neq j} P_{tx(k)} \cdot h_{ki} + \sum_{m \in STA_{active}} P_{tx(m)} \cdot h_{mi} \tag{4}$$

where h_{ki} and h_{mi} represent the channel gains from the interfering AP and STA, respectively, and STA_{active} denotes the set of STAs actively transmitting. The expression for the uplink transmission from STA_i to AP_j is given by (5).

$$SINR_{UL(i,j)} = \frac{P_{rx(j,i)}}{N_j + I_j} \quad (5)$$

The main difference in the uplink calculations is that STAs usually transmit at a lower power. This increases the probability of collisions, owing to the distributed properties of the CSMA/CA protocol.

V. EXPERIMENTAL ENVIRONMENT

In this study, experiments were conducted to analyze the impact of increasing traffic load on network performance by varying the data transmission rate to 3, 6, 12, 24, and 48 Mbps in a formula-based simulation using MATLAB 2021b [12]. Experiments lasting 10 s were repeated 1000 times for each traffic load level to measure the average performance. A ML model using XGBoost [13] was employed to predict and control TX power and RX sensitivity based on the network environment. The model was divided into two approaches: a centralized method, where a single AP handles data learning and prediction, and a distributed method, where nine APs perform data learning and prediction across a 40 m area. The experiments compared and analyzed the following four approaches:

TABLE II. CONTROL TECHNIQUES

Control techniques	Description
Conv (central)	Conventional method controlling Tx power in a centralized technique
Conv (dist)	Conventional method controlling Tx power in a distributed technique
Prop (central)	Proposed method controlling Tx power and Rx sensitivity in a centralized technique
Prop (dist)	Proposed method controlling Tx power and Rx sensitivity in a distributed technique

Table 2 summarizes the control techniques used as comparators in this experiment. Conv (central) is a conventional method that centrally controls TX power, corresponding to the approach by Wojnar et al. [7]. Conv (dist) is a conventional method for controlling TX power in a distributed manner. Prop (central) and prop (dist) are the proposed methods for controlling Tx power and Rx sensitivity in centralized and distributed manners, respectively.

The performance evaluation metrics used were the effective throughput, SINR, control overhead. To evaluate network performance, the achievable effective throughput of each STA-AP link was measured. Effective throughput follows the IEEE 802.11ac physical layer specification, with the transmission rate adaptively selected based on the channel quality [14]. The effective throughput T_i of each STA_i is calculated using (6).

$$T_i = R_{MCS}(SINR_i) \times (1 - PLR_i) \quad (6)$$

where $R_{MCS}()$ is the MCS selection function that maps the measured SINR to the corresponding data transmission rate. The IEEE 802.11ac standard defines 10 MCS levels (0–9), supporting rates from 6.5 Mbps (MCS 0, SINR $\geq$ 5 dB required) to 86.7 Mbps (MCS 9, SINR $\geq$ 33 dB required) on a 20 MHz channel. This function selects the highest MCS level that satisfies the minimum SINR requirement. PLR_i is the PLR that combines channel-induced errors and collision-induced losses, as shown in (7).

$$PLR_i = PLR_{channel}(SINR_i) + PLR_{collision(\rho)} - PLR_{channel} \times PLR_{collision} \quad (7)$$

where ρ represents network congestion. STAs with an SINR below 5 dB experience high packet loss (50–90%), whereas those with an SINR above 20 dB achieve low loss rates (below 5%). The control overhead represents the time required for parameter optimization, including ML prediction, file I/O, and SINR calculation. This is distinct from the data transmission period used in effective throughput measurements. While the distributed method theoretically allows nine APs to operate independently, our MATLAB implementation processes these operations sequentially, resulting in cumulative overhead.

VI. PERFORMANCE EVALUATION

In this section, the performance of the proposed ML-based joint control technique is evaluated. The centralized and distributed schemes are compared with the conventional methods, focusing on effective throughput, control overhead, and measured SINR under various traffic load conditions. Figure 4 shows the effective throughput of each method for different traffic loads.

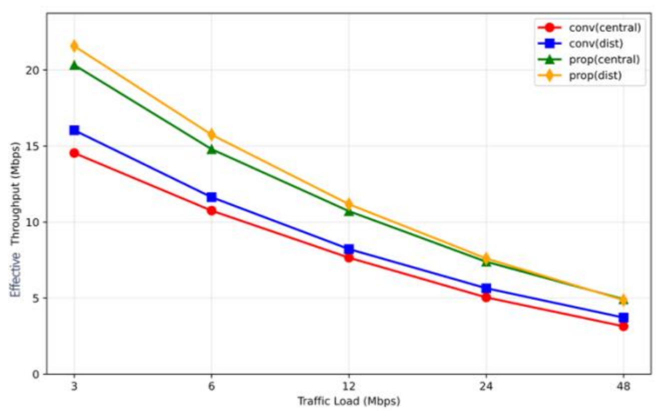

Figure 4. Effective throughput comparison of the four control schemes (conv (central), conv (dist), prop (central), and prop (dist)) with increasing traffic load.

As the traffic load increased, the effective throughput decreased across all methods. The prop methods (central, dist) demonstrated superior performance compared with the conv methods (central, dist). Specifically, prop (dist) achieved the highest effective throughput of 12.09 Mbps, showing an improvement of approximately 47.1% over conv (central). This improvement results from the effective interference control achieved by simultaneously optimizing TX power and RX sensitivity. The dist method exhibited higher effective throughput than the central method because each AP was optimized with values suitable for a 40 m radius area, enabling finer control. At a low traffic load (3 Mbps), prop (dist) achieved the highest effective throughput at 21.43 Mbps, representing a performance improvement of approximately 46.4% compared with conv (central). However, as the traffic load increased to 48 Mbps, the interference caused a sharp decrease in effective throughput for all methods. Notably, prop (dist) exhibited an effective throughput of 4.71 Mbps, which was 0.44 Mbps lower than that of prop (central).

Figure 5 shows the results of the comparison of the control overhead for each method.

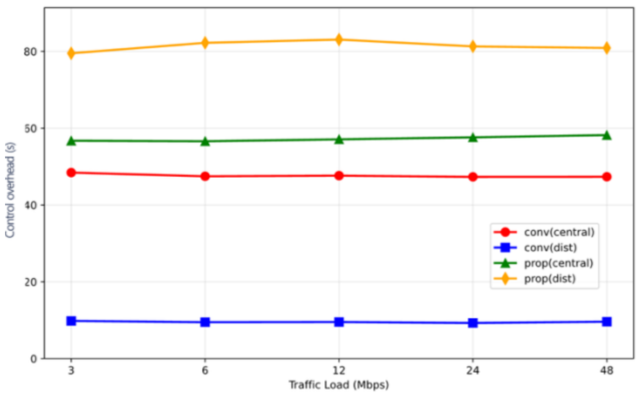

Figure 5. Control overhead comparison of the four control schemes (conv (central), conv (dist), prop (central), and prop (dist)) with increasing traffic load.

Conv (dist) exhibited the fastest control overhead, averaging 9.8 s, whereas prop (dist) required the longest control overhead, averaging 80.6 s. All the methods maintained consistent control overhead regardless of the traffic load, because the computational complexity of the algorithm was independent of the data transmission rate. Because of the complex model structure that simultaneously optimizes TX power and RX sensitivity, the control overhead for the prop methods (central, dist) increased compared with those of the conv methods (central, dist). Specifically, prop (dist) used four models, significantly increasing the overhead and requiring additional computation to predict both TX power and RX sensitivity based on network state information. However, in actual distributed systems, each AP operates independently; therefore, the benefits of parallel processing exist from the perspective of the entire network. Prop (central) increased by 18.1% compared with conv (central), averaging 57.5 s, whereas prop (dist) increased by 723.2% compared with conv (dist).

Figure 6 shows the SINR variation for each method under different traffic loads.

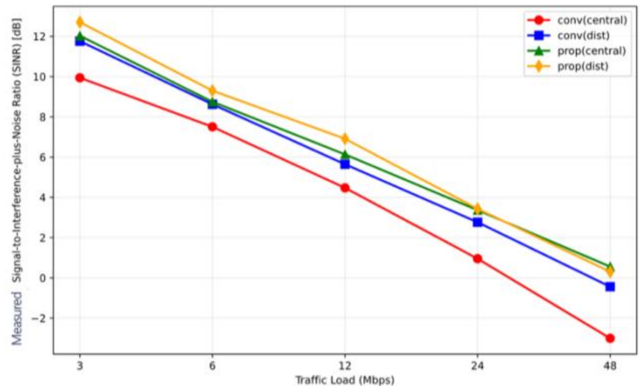

Figure 6. Measured SINR comparison of the four control schemes (conv (central), conv (dist), prop (central), and prop (dist)) with increasing traffic load.

The experimental results indicate that the prop method generally maintained a higher SINR than the conv methods (central, dist). Prop (dist) achieved the highest average SINR of 6.09 dB, representing a 29.6% improvement over conv (central). As the traffic load increased, all methods exhibited a decreasing trend in SINR. When traffic load increased from 3 to 48 Mbps, conv (central) decreased from 10.76 to -1.65 dB, and conv (dist) decreased from 11.61 to -0.73 dB. The proposed methods, prop (central) and prop (dist), also decreased from 11.66 to 0.28 dB and from 12.06 to -0.05 dB, respectively. However, even under high traffic load, the proposed methods maintained a relatively high SINR, providing better link quality. This demonstrates that the proposed methods can sustain a stable link quality even in high-traffic-load environments. The analysis indicates that the distributed approach maintains a higher SINR than the centralized approach because it can more accurately identify and control the interference characteristics within the local area.

VII. CONCLUSION AND FUTURE WORK

The rapid increase in the number of devices utilizing wireless networks has exacerbated problems such as channel interference, degraded network quality, and jamming attacks in OBSS environments. Previous studies avoided interference by suspending communication on some links or applying time-division methods; however, these methods failed to reflect real-time changes in the network environment, limiting improvements in overall throughput and SR rates. To address these issues, this study proposes an ML-based simultaneous control technique for TX power and RX sensitivity. The proposed technique is implemented in both the centralized and distributed architectures. Each node recognizes the network state and then predicts and applies the optimal parameters through an ML model, effectively controlling the interference. Experimental results demonstrate that the proposed technique achieves up to 47.1% higher effective throughput and 29.6% improved measured SINR compared with conventional techniques. In particular, the proposed distributed approach achieved a 46.4% higher effective throughput than the proposed centralized approach under low traffic load conditions while maintaining a relatively stable link quality even under high traffic loads. Although the control overhead increased significantly in the proposed distributed approach, the distributed structure enabled each AP to operate independently. This leverages the benefits of parallel processing, ensuring practical applicability in real-world environments. However, limitations were identified in the simulation environment. MATLAB is primarily designed for algorithm development and numerical computation, not for network simulation, and could not adequately reflect the parallel nature of distributed systems. The sequential processing of distributed operations in MATLAB resulted in higher control overhead, which prevented the observation of actual performance benefits that would occur when multiple APs operate independently in real networks. Future research will use ns-3 for more realistic distributed simulations and reinforcement learning for adaptive control, ultimately validating the framework in real WLAN scenarios.

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