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Developing A New Scheduling Algorithm for Wi-Fi 6 Technology Based on Machine Learning

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Abstract

Wireless mobile communications have experienced tremendous growth in the number of users, data rate requirements, and coverage in recent years. As the data rate and system throughput requirements increase, researchers and system designers need to develop efficient methods to meet these requirements with reasonable effort and cost. In this paper, we discuss an efficient approach to deal with diminishing the overhead of Downlink (DL) and feedback using Machine Learning (ML) for 802.11ax. In particular, the antennas that are related to the router were divided into two gatherings. We used good samples of Channel State Information (CSI) that were taken from an open-access dataset and used it to train our linear regression model. The first group of antennas was used as input to our model and the second group was used as the output of the model. In the online mode, we need to estimate only one group of antennas and for the second group, we can predict it using the trained linear regression model by using the estimated CSI group as input to the model. Therefore, the output of the model using as the CSI for the second group. In this way, we can reduce the overhead of the DL in the router as shown in the result table so the router will work more efficiently compared to the existing systems. From the results table in the last section, the average sum rate has increased between 20% and 30%.

Key Words

“802.11ax Standard, Wireless Network, Wi-Fi 6, Leaner Regression, Machine Leaning, Scheduling Algorithm”

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1. Introduction

The Internet has been dominated by things we could not live without, according to an Opinium Research online survey conducted by Direct Line, which asked some people to rank the things you could not live without. Some of those things were family, food, TV, cars... and more. Of course, Wi-Fi (Internet) was also one of those things. The result is shown in Figure 1. We can see that when asked "How important is Wi-Fi in (daily) life?" so these days, when we move to a new house the first thing that we think about it is the Internet. therefore we are spending a large time surfing the Internet more than the time than spending it with our family or eating food,, with the rule nowadays being "No Wi-Fi, no homework"(Thomas, 2015; Newsroom, 2014).

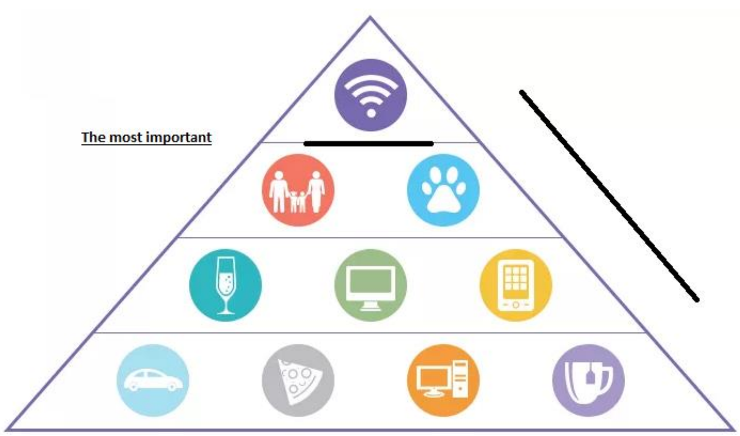

Figure 1. Important things in the people's live (Thomas, 2015)

We use the Internet on portable devices such as smartphones (cell phones), tablets, or PCs. To make it more convenient for us, we use Wi-Fi instead of using wired connections like Ethernet. In fact, we make connections with a device connected to the Internet called a 'router'. Wi-Fi uses radio waves to transmit data on specific frequencies, usually on 2.4 GHz and 5 GHz. Multiple channels, referred to as the frequency range in which wireless devices can operate, help to spread the load so that signals from individual devices are not overloaded or interrupted by other traffic, although this does happen in busy networks (Newsroom, 2014; Stallings & Beard, 2016).

Wi-Fi has become ubiquitous in our lives: in universities, homes, stadiums, subways, meetings, and more. As mentioned earlier, we connect to a router through which we can use the Internet. So we need to find a good scheduling algorithm to make the router work fast and improve its efficiency and quality of service (QoS) (Stallings & Beard, 2016; Lodwal et al., 2019; Gopalan, Caramanis, Shakkottai, et al., 2012).

Starting from this topic, we come to the concept of MIMO, which means "multiple-input multiple-output," where the router can serve multiple users simultaneously. The concept of multiple-output is so important in making Wi-Fi more efficient and faster. It was developed during the generations of the Wi-Fi (Stallings & Beard, 2016; K. Lee & Kim, 2015).

In order to develop efficient algorithms for MIMO user scheduling, the following two concepts must be mentioned:

- Orthogonal Frequency Division Multiplexing (OFDM): or named multicarrier modulation. each channel has multiple carrier signals on the frequency domain but in the same period, it used to transmit just the packets are related to one user as shown in Figure 2.

- Orthogonal Frequency Division Multiple Access (OFDMA): it is a type of multi-user version of the OFDM digital modulation plan. Here multiple access is accomplished in OFDMA by allocating subsets of subcarriers to particular managers. Therefore, it transmits packets by using the frequency and time domains together as presented in Figure 3.

The last generation of Wi-Fi, called IEEE 802.11ax, used OFDMA technology. 802.11ax therefore provides for the introduction of OFDMA into Wi-Fi first. It allows the use of multiplexing users in the frequency range (Afaqui et al., 2016; Omar et al., 2016; Wang & Psounis, 2018).

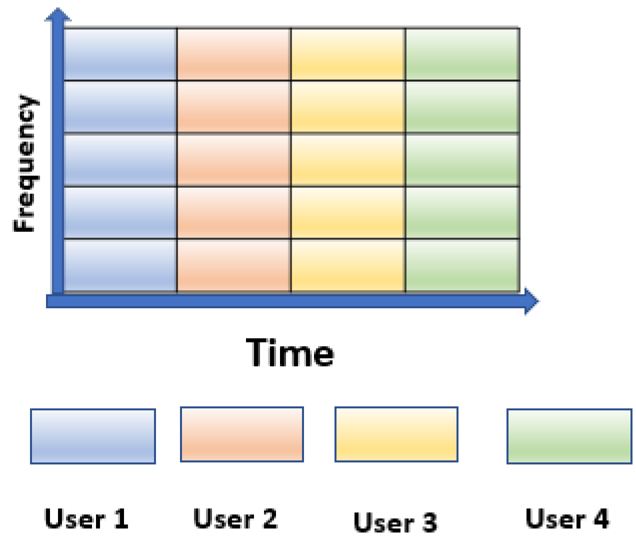

Figure 2. OFDM scheme

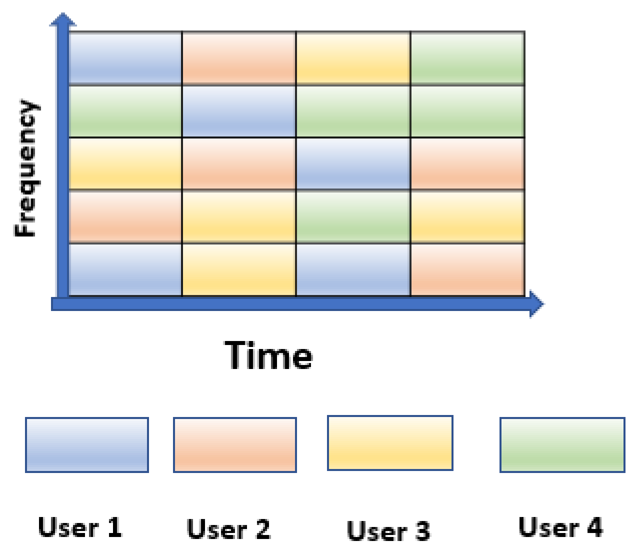

Figure 3. OFDMA scheme

In IEEE 802.11ax, subcarriers are isolated into Resource Units (RUs) for scheduling. Thus, the bandwidth contains subsets of subcarriers, all of which are called RUs. We can also say that the RU is a group of sections called “tones” assigned to a station (STA). The size of the RU has a certain number of tones according to IEEE 802.11ax. The amount of RUs available depends on the channel width (CISCO(team), 2018; Wang & Psounis, 2018; Karthik & Palaniswamy, 2018).

Nowadays, machine learning (ML) has a great importance in different areas of life, where it receives enormous attention in both industry and academia due to its ability to analyze data and make fast and accurate decisions (Bi et al., 2015). So, to find an optimal algorithm for user scheduling in Wi-Fi, we should think about working with ML, where ML has shown great utility in solving some problems in wireless communication, as we will see in the literature section.

This work concentrates on developing a novel resource distribution and scheduling algorithm in a downlink based on artificial intelligence for Wi-Fi 6, and tests it using MATLAB and the network simulator ns-3. The capability of ML is used to quickly analyze data and make appropriate decisions to obtain a more efficient and effective algorithm in crowded systems. Our basic idea is to combine ML, which achieves the best efficiency, with a previous resource scheduling and allocation algorithm based on Wi-Fi 6 to develop a new, more efficient algorithm.

The remainder of this article is organized as follows. Section 2 specking about previous work. In Section 3 presents a technical background that contributes to the understanding of our work. While in Section 4, we present our new resource allocation and scheduling algorithm based on the submitted materials and methods. Simulation results are shown in Section 5. In Section 6, we are showing a conclusion of our work.

2. Related Work

One of the critical issues in wireless networks is management and resource allocation to achieve more effective throughput and perfect fairness among users, where throughput and fairness are traditional benchmarks for evaluating the performance of a wireless network. Therefore, there are a lot of studies on this topic to improve the performance of the wireless network (Pilosof et al., 2003; Bottigliengo et al., 2004; Bhagwat et al., 1996; Urvoy-Keller & Beylot, 2008; Yao et al., 2015).

From the perspective of previous studies on new techniques of wireless planning, they can be mainly divided into the following categories:

2.1. Cellular Network Scheduling Based

Mobile networks are constantly being developed to make them more efficient and suitable for applications with high data rates. The most important technology used in this perspective is Long Term Evolution (LTE). Packet scheduling algorithm in LTE/LTE Advanced has been well studied in previous work (Tabany & Guy, 2015; Md Zain et al., 2015; Zubairi et al., 2015; Baghi & Daneshvar Farzanegan, 2015; Liu & Chen, 2015; Shukla & Bhatia, 2018; Bazzi et al., 2019; Huang et al., 2019; Uyan & Gungor, 2019). In (Shukla & Bhatia, 2018), the work was about reducing high packet loss and improve it, which will improve the QoS, by made an algorithm dependent on packet priority. In (Bazzi et al., 2019) on the other hand, the new technology IEEE 802.11 p, which includes LTE, was studied and compared with LTE direct vehicle-to-vehicle (LTE-V2V) communication in the article "Analytical Investigation of Two Benchmark Resource Allocation Algorithms for LTE-V2V".

In (Huang et al., 2019), on the other hand, the issue was Carrier-Sensing Adaptive Transmission (CSAT), that affects the synchronization of LTE and Wi-Fi in unlicensed spectrum. The main problem between LTE and Wi-Fi is that radio resources need to be shared among multiple channels and many sub-channels, so the solution is to develop an optimal scheduling algorithm to allocate radio resources in real time. Thus, the UL and DL rate constraints of each LTE user could be met by optimally allocating radio resources at the sub-channel and channel level.

2.2. Wi-Fi Scheduling Based

Because of the importance of this issue, Wi-Fi scheduling has been well studied in previous work. We have a problem of measuring the execution of the scheduling algorithm in Wi-Fi, where efficiency and fairness are the most important measures of the performance of any Wi-Fi scheduling algorithm. To improve the performance of Wi-Fi, we need to achieve high efficiency and high fairness, which are often in conflict with each other. In other words, more efficiency leads to less fairness and vice versa (Lodwal et al., 2019; Yao et al., 2015; Tabany & Guy, 2015; Pantelidou & Ephremides, 2009; Walrand, 2010).

2.2.1. Packet scheduling

In (Yao et al., 2015) presents a new algorithm used for packet scheduling, called DAT in a crowded 802.11 WLAN. This work allows access points (APs) to automatically modify the time windows for supplying each active WLAN, dynamically shifting the weight between fairness and efficiency.

In (Gabale et al., 2013), on the other hand, an overview of scheduling algorithms in wireless mesh networks was given. In (Das et al., 2013), an overview of the most suitable scheduling algorithm for WIMAX-Wi-Fi was also given. Here in (Kathrine & Raj, 2012) an overview of packet scheduling in different networks has been done. Designs the RAS algorithm by fully utilizing the high-speed channel rate of an 802.11 n Wi-Fi router (Han et al., 2015).

To improve the efficiency of Wi-Fi, consideration was given to how we could serve multiple clients simultaneously. Initially, a technique was thought of to send packets from one transmitter to multiple receivers by using multiple antennas at the transmitter AP. So, in (Zhang et al., 2013), the study was concerned with the "one-sender-multiple-receiver (OSMR)" transmission technique. After that, attention was focused on a new technique called Multiple Multiple-Input and Multiple-Output (MIMO), which includes two types: Multi-user-Multi-input-Multi-output (MU-MIMO) transmission and Single-user-Multi-input-Multi-output (SU-MIMO) transmission. In (K. Lee & Kim, 2015), a new MU-MIMO MAC protocol called 802.11ac+ is proposed, which includes a novel user scheduling algorithm that uses channel hint-based polling and active CSI feedback. The algorithm determines the best user set during the CSI feedback phase so that AP does not receive CSI from all users, thus obtaining more efficiency. In (Shen et al., 2015), a novel MU-MIMO MAC, called SIEVE, is presented to search for the best group. Where in (Gopalan, Caramanis, & Shakkottai, 2012) selecting subsets with the largest queue sum of squares followed by selecting a user with Max-Weight within the subset is throughput optimal with CSI.

2.2.2. Power scheduling

Improve AP and client power consumption by tuning AP to allow clients to remain in low-power mode whenever possible to consume less power. Due to the importance of an energy-efficient Wi-Fi network, energy-efficient scheduling in AP has been well studied in the literature (Anand et al., 2005; Rozner et al., 2010; Dogar et al., 2010; Manweiler & Roy Choudhury, 2012; Enayet et al., 2016). This paper focuses on scheduling and resource allocation on Ap in Wi-Fi 6, where energy saving mode is not enabled.

2.3. 802.11ax Scheduling Based

The 802.11ax is a new technique in the Wi-Fi with OFDMA and Multi-User Multiple Inputs Multiple Outputs (MU-MIMO), so most previous work was to explore the difference that exists at the physical layer and energy saving advances through the tutorial (Khorov et al., 2019; Bellalta & Kosek-Szott, 2019), surveys (Qu et al., 2019) and the main challenges (Afaqui et al., 2016), performance analysis (K. H. Lee, 2019a), QoS evaluation (Sanchez-Mahecha et al., 2018), and solving some of the problems faced by the IoT when using 802.11ax (Kwon et al., 2018).

Also, in previous work, researchers had developed some scheduling algorithms for different objectives, such as maximizing user sum rate (Wang & Psounis, 2018), maximizing QoS throughput (Chao et al., 2015; Islam & Kashem, 2019), and trying to reduce real-time delay to less than one millisecond (Avdotin et al., 2019). Some scheduling algorithms have been developed using different techniques, such as in (Afaqui et al., 2015) based on the average received signal strength, this algorithm dynamically adjusts the carrier sense threshold (CST) using an adaptation of IEEE 802.11e Enhanced Distributed Channel Access (EDCA) (Karthik & Palaniswamy, 2018) based on a wireless distributed computing system (Ramji et al., 2014) based on multi-user transmission (Ghanem et al., 2019). In (K. H. Lee, 2019b), the AP estimates and collects multiple CSI values from the uplink OFDMA framework. Where in (Li et al., 2018) scheduling video streaming.

Some previous works addressed the optimization of resource allocation and scheduling algorithms in the downlink through many methods, such as the Lagrangian dual decomposition method (Seong et al., 2006), TCP goodput optimization (Sharon & Alpert, 2018), and the use of nonorthogonal multiple access (NOMA) schemes (Tseng et al., 2020).

Some work addressed improving scheduling in the uplink by minimizing delay (Bankov et al., 2017; Bankov et al., 2018) and improving scheduling strategies for TCP traffic (Sharon & Alpert, 2019). While in (Naik et al., 2018) the performance analysis of uplink multi-user OFDMA and in (Sharon & Alpert, 2017) the scheduling strategies and throughput optimization were explained. Here In (Dovelos & Bellalta, 2018), the original stochastic utility maximization problem is solved while throughput is maximized (Bhattarai et al., 2019).

2.4. Wi-Fi Scheduling with ML Based

In (Cui et al., 2019), a deep learning methodology was applied to circumvent channel estimation and efficiently schedule links based solely on the geographic locations of transmitters and receivers, eliminating the costly channel estimation phase. In (Cao et al., 2018), Deep Belief Networks (DBNs) and Support Vector Machines (SVMs) were applied to develop an optimal algorithm for scheduling and power control. In (Dong et al., 2018), Support Vector Regression (SVR) and LR are used to reduce the overhead of downlink channel estimation and feedback by dividing the indices of antennas at the base station (BS) into two groups. The estimation (prediction) of CSI in the second set is then done using CSI, which was considered in the first set. In (Ye et al., 2018), Deep Learning is used for signal detection and channel estimation OFDM structures. And in (Utami & Iskandar, 2019a) using Genetic Algorithm for Resource Allocation in OFDMA and using Genetic Algorithm to resource allocation Analysis in LTE MIMO-OFDMA Cellular System (Utami & Iskandar, 2019b).

Another direction in previous work is to improve throughput and fairness using an online learning-based methodology over a unified logical control design. In (Karmakar et al., 2019), a reinforced learning strategy is used to dynamically select the most appropriate configurations at regular intervals to obtain optimal intellectual MU-MIMO user choice with connection modification.

3. Technical Background

3.1. Wi-Fi History

In the table 1 we can see the major different between the standards of Wi-Fi and give a brief overview of the most recently accepted technologies outlined from the past to the present. Other technologies (802.11ax), 802.11ay and 802.11az- are still in the research process.

Wi-Fi 6 is the latest form, as famous as 802.11ax, and it will be standardized in 2019. It will increase speed and reduce latency by about 30 percent. The main point is that it can provide more data to each device at the same time. It can be used efficiently where there are many devices, such as at trade shows, press conferences, stadiums, and the like. Due to the increase of data and devices, stronger networks will be needed in the future.

Table 1. The major different between the standard Wi-Fi

Name of Wifi	Year	Data Rate (Mbps)	Frequency Band	Chanel Bandwidth	Modulation Signal Encoding	Spectrum Protocol	Antenna Configuration
802.11a	1999	54	5 GHz	20 MHz	64 QAM	OFDM	1X1 SISO
802.11b	1999	11	2.4 GHz	20 MHz	11 CCK	DSSS	1X1 SISO
802.11g	2003	54	2.4 GHz	20 MHz	64 QAM	DSSS, OFDM	1X1 SISO
802.11n	2000	65- 600	2.4 or 5 GHz	20,40 MHz	64 QAM	OFDM	4X4 MIMO
802.11ac	2012	78-3.2 Gbps	5 GHz	40,80,160 MHz	256 QAM	SU-OFDM	8X8 MIMO, MU-MIMO
80.11ad	2014	6.76 Gbps	60 GHz	2160 MHz	64 QAM	SU-OFDM	1X1 SISO

3.2. Wi-Fi MU-MIMO System

MU-MIMO increases wireless capacity because AP can send packets to multiple users simultaneously (beamform) by equipping them with multiple antennas. The important question in this technique is "How do we select the user group to process in real time in the scheduling process?", or in other words, we select the beamforming group. An incorrect method of selecting a sending group can result in decrease the data rates and decrease capacity instead of improving it. To find a better beamforming group, we need to calculate the CSI array, which contains the data about the status of the links between the users' antennas and the AP antennas (Shen et al., 2015).

3.3. Wi-Fi Scheduling and Resource Allocation Problem (SRA)

In wireless systems, resources such as sending signals and transmit power are restricted, so resource management and allocation is constantly a crucial problem. In recent years, this issue has become more complex with new techniques such as Long-Term Evolution (LTE), MIMO, MU-MIMO, OFDM and OFDMA (802.11ax). Here we have small channels called subcarriers and RU. Our task is to determine the size and location of these subcarriers and then consider how best to distribute users (user groups) across these subcarriers. Therefore, there are many works in the literature to solve this problem, and due to the conditions of each standard, we cannot apply the scheduling algorithm to all of them. For example, in the LTE scheduling algorithm, the user can assign multiple subchannels and the area of the subchannels can be change, while the location of the RUs is restricted and only a single RU can be allocated to a user in the 802.11ax algorithm (Wang & Psounis, 2018; Bhattarai et al., 2019).

3.4. LR model in ML

ML was launched in 1950 and means that a computer can learn from input data by preprocessing the data and extracting features from it to use as a training set. So, the ML process involves input data (dataset) from which we then extract the features and then build our prediction model or classification model. There are several types of ML: Supervised ML, here we have input and output used in prediction and classification problems. Unsupervised ML, here we have only input which is used in clustering. In regression model, we have a set of data as input which are related to each other. After we have processed the input data and obtained the model, if we input new data into the model, we can regress the desired result.

3.5. 802.11ax Standard

802.11ax supports this type of transmission in Wi-Fi: MU-MIMO, OFDMA and MU-MIMO & OFDMA together. 802.11ax comes with several features: OFDMA, MU-MIMO, Overlapping Basic Service Set (OBSS), Target wake Time (TWT), 1024 QAM modulation and longer OFDM symbols. We will explain some of them:

OFDMA is a multiple access technique based on orthogonal frequency division multiplexing (OFDM). OFDM and OFDMA divide the entire bandwidth into small subchannels called subcarriers. The difference between OFDMA and OFDM is that in OFDM, a single user is assigned all subcarriers, whereas in OFDMA, a user or group of users is assigned only a subset of subcarriers, called RU, and data is transmitted only on that RU. Thus, in this way, a frame can multiplex multiple users or user groups simultaneously. The bandwidths 20MHz, 40MHz, 80MHz, 80+80MHz, and 160 MHz are supported by 802.11ax (CISCO (team), 2018; Wang & Psounis, 2018). As we mentioned earlier, OFDMA transmission divides the bandwidth into multiple RUs. Then, the RUs can be divided smaller and smaller, up to 26 subcarriers, and the size of RUs in the frequency domain can be: 26, 52, 160, 242, 484, or 996 subcarriers (Khorov et al., 2019). Figure 4 presents the positions of RUs in a 40MHz example HE PPDU.

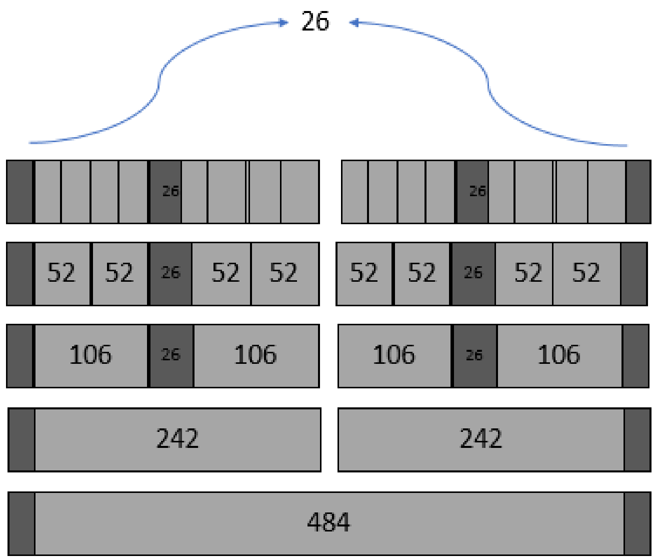

Figure 4. RU locations in a 40MHz HE PPDU

4. Material and Methods

4.1. Estimation and prediction of CSI

To estimate the CSI as a function of the CSI to devices connected to the same AP in real time, we need to build an estimation model. To build the estimation model, we can divide the process into three steps, as we can read in reference (Dong et al., 2018).

- **Offline regression model training**:

We used a well estimated CSI as a dataset. Let H be the CSI array between the AP antennas and users' antennas be the training set matrix based on Least-square (LS) and during N channel realizations $H = [h_1^T, \dots \dots \dots, h_N^T]^T$. Then we divided the list of antennas at the AP into two subsets, A and B. Let $U = \{1,2, \dots, M\}$ be the set of the antennas in the AP, where $A \cup B = U$ and $A \cap B = \emptyset$ and the $A(i) = U(A(i)$ and $B(i) = U(B(i))$.

After that we divide the H matrix into two submatrices as $H_I = [H]^A$ and $H_O = [H]^B$. We will define two regression model M_i^{Re}, reveals the relationship between the CSI of the antennas in A and the real part of the CSI of the $B(i)$th antenna and M_i^{Im}, reveals the relationship between the CSI of the antennas in A and the image part of the CSI of the $B(i)$th antenna:

$[Re\,\{H_I\}\,, Jm\{H_I\}\,]$ as input to M_i^{Re} model and the real part of ith column of H_O. That mean $Re\{H_O(:,i)\}$ as output to M_i^{Re} model.

$[Re\,\{H_I\}\,, Jm\{H_I\}\,]$ as input to M_i^{Im} model and the real part of ith column of H_O. That mean $Jm\{H_O(:,i)\}$ as output to M_i^{Im} model.

Let $\breve{h}_{n,A} = [Re\,([h_n]^A)\,, Jm\,([h_n]^A)] \in R^{1\,X\,2\,|A|}$ the LR model, where the equation of get predict value of real part of the CSI of the $B(i)$th antenna is given by: $f\,(\breve{h}_{n,A}) = \breve{h}_{n,A}\,\alpha_i + \beta_i, \qquad i = 1, \dots, |B|$

In a more Tractable way to training the LR. Let $H_I = [Re\,(H_I), Jm\,(H_I), 1] \in R^{N\,X\,(2\,|A|+1)}$ and $K_i^{Re} = [\alpha_{i1}, \dots, \alpha_{(2|A|)}, \beta] \in R^{N\,X\,1}$. Then the last equation becomes: $f\,(H_I(n,:)) = H_I(n,:)K_i^{Re}, \qquad i = 1, \dots, |B|$

Then the optimal $K_i^{Re,*}$ is given by: $K_i^{Re,*} = (H_I^T H_I)^{-1}\,H_I^T\,Re(H_O(:,i))$. The optimal $K_i^{Im,*}$ is given by:
$K_i^{Im,*} = (H_I^T H_I)^{-1}\,H_I^T\,Jm(H_O(:,i))$

- **Online CSI Estimation:**

Here in this step, the user can get the CSI related to the antennas in the A group by applying the LS model prediction as: $\breve{h}_A = yX^H(X\,X^H)^{-1}$. Then the calculated $|A|$- channel vector, $\breve{h}_A$, is send to the AP. Let $\hat{h}_A$ be the channel vector feedback snding by the user.

- **Online CSI Prediction:**

As we mentioned above, the $\hat{h}_A$ will selected to guess CSI of transmitters in B as $\hat{h}_B$:$\hat{h}_B(i) = M_i^{Re}([Re\,(\hat{h}_A), Jm(\hat{h}_A)]) + j\,M_i^{Im}([Re\,(\hat{h}_A), Jm(\hat{h}_A)])$.

4.2. User Grouping of MU-MIMO:

As we mentioned earlier, unwise selection of beamforming groups can lead to a reduction in overall capacity rather than an increase in it. Here, the large search space presents a challenge. Therefore, to find the best beamforming group, we need more complex algorithms. We will use the SIEVE user selection algorithm that searches for the best beamforming group. The user selection of SIEVE keeps a small set of good candidates at a time, depending on the general branch-and-bound algorithm, and then iteratively refines this candidate set. Figure 5 presents the enumeration tree of the procedure to solve the problem, where each vertex in the i-level of the tree is a subset of users of size i. The subset of users is the number of users in the i-level of the tree. The subset includes the users selected along the branch to the root. Then, only the top K candidates in each branch level are kept and the bad combinations are filtered out (Shen et al., 2015).

4.3. 802.11ax Scheduling Algorithm

As mentioned earlier, the 802.11ax standard has high efficiency compared to the old standards due to the use of OFDMA. The frequency band is separated into several RUs that have a certain size. We will use the recursive scheduling algorithm described in (Wang & Psounis, 2018) by 'kaidongw and kpsounis'. The pseudocode of the algorithm is shown in Figure 6. As mentioned earlier, the 802.11ax standard has high efficiency compared to the legacy standards by using OFDMA. The frequency band is divided into several RUs, which have a certain size. We will use the recursive scheduling algorithm described in (Wang & Psounis, 2018) by 'kaidongw and kpsounis'. The pseudocode of the algorithm is shown in Figure 6.

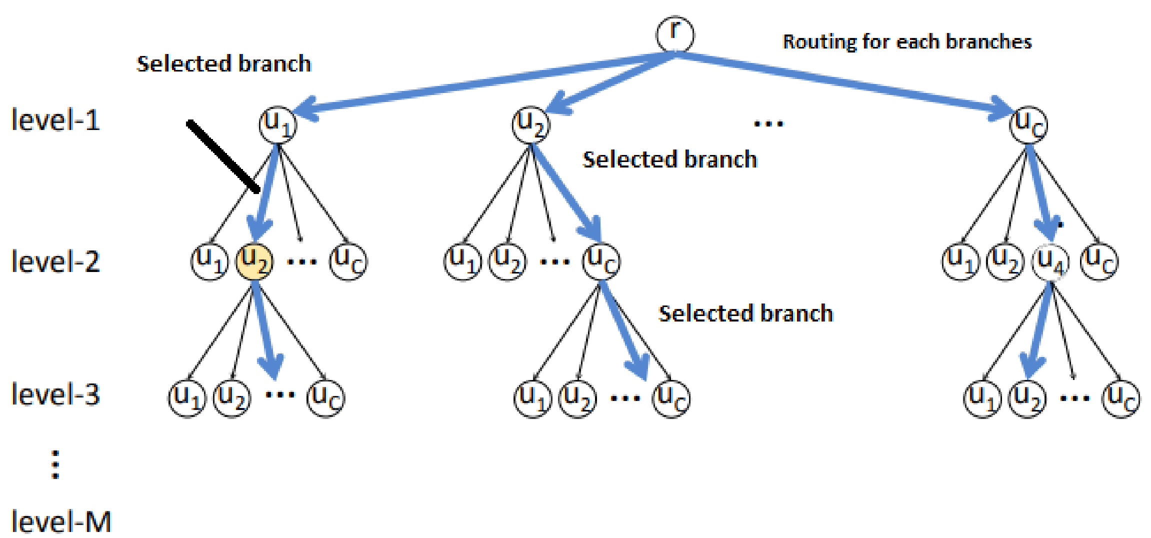

Figure 5. SIEVE search tree (Shen et al., 2015)

4.4. Propose Algorithm

First, we divided the antennas of AP into two subgroups and then estimated the CSI of the first group (calculated in the usual way). Then we used CSI of the first subset as input to the regression model to predict the CSI for the second subset, as shown in Figure 8. In this way, we now have the CSI of all antennas. Then we applied the 802.11ax planning algorithm, as shown in Figure 6, and applied the user selection method for the RUs equal to or greater than 106 subcarriers. The pseudocode is shown in Figure 7.

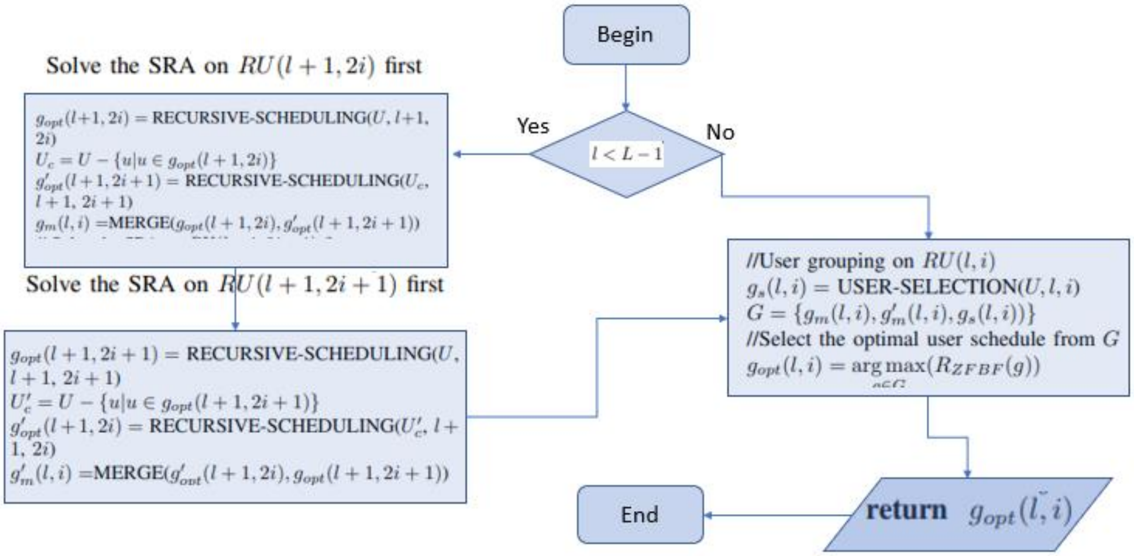

Figure 6. Pseudo code of recursive-scheduling algorithm (Wang & Psounis, 2018)

1: //divide the AP antennas into two subsets

2: // let M number of antennas in the AP and the subsets are A, B

3: // Let H_A be the CSI of the first subset A

4: $H_A = [Re\{H_A\}, Jm\{H_A\}]$

5: // Calculate the H_B by applied the regression model as shown in the online CSI prediction

6: $H_B = M_i^{Re}([Re(H_A), Jm(H_A)]) + j\, M_i^{Im}([Re(H_A), Jm(H_A)])$

7: // CSI of all antennas are ready now to apply as input in the 802.11ax scheduling Algorithm

8: Recursive-Scheduling (U, l, i)

Figure 7. The pseudocode of proposed algorithm

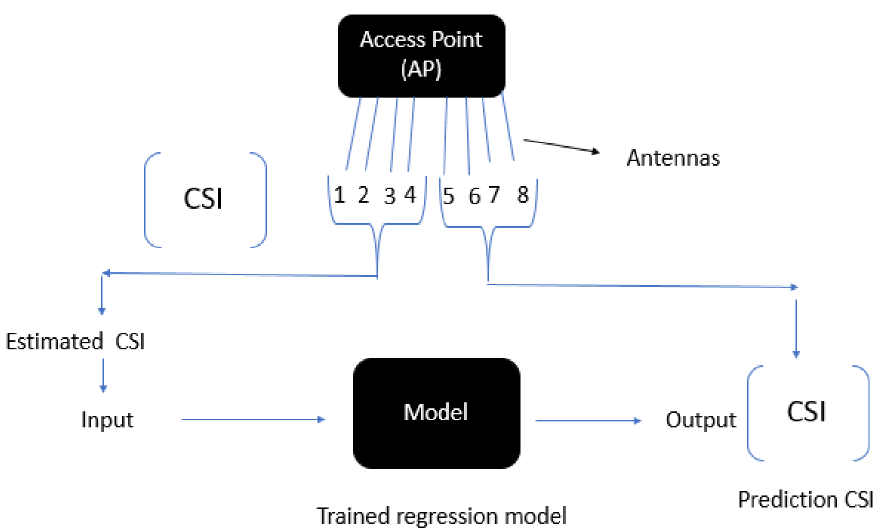

Figure 8. CSI prediction Steps

5. Simulations

The old and new algorithms are evaluated in simulations. The example of 802.11ax RUs split with the "WlanHEMUConfig" object. In Figure 9, the 40 MHz bandwidth is split into 4 RUs, each of which has 106 subcarriers. In Figure 10, the 20 MHz bandwidth is split into 9 RUs that have the same size of 26 subcarriers, and in Figure 11, the 20 MHz bandwidth is split into 3 RUs, where two RUs have 52 subcarriers and the third has 106 subcarriers.

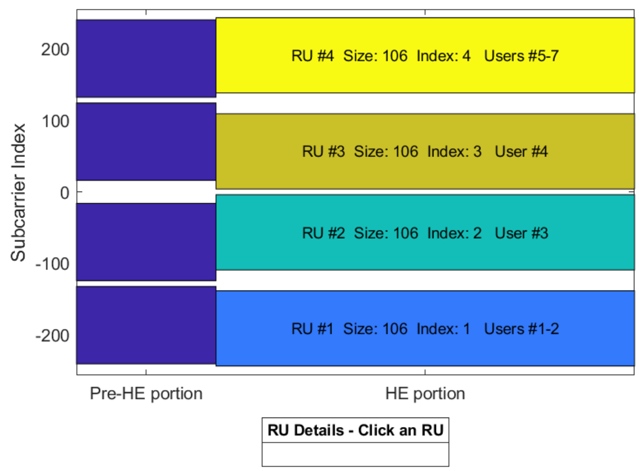

Figure 9. 40MHz, 4 RUs (106)

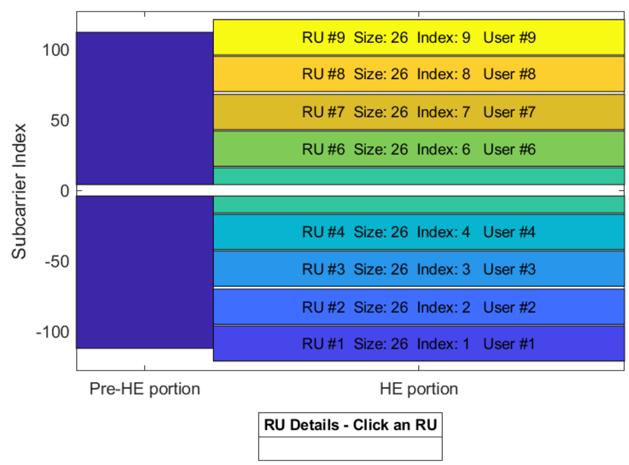

Figure 10. 20MHz, 9 RUs (26)

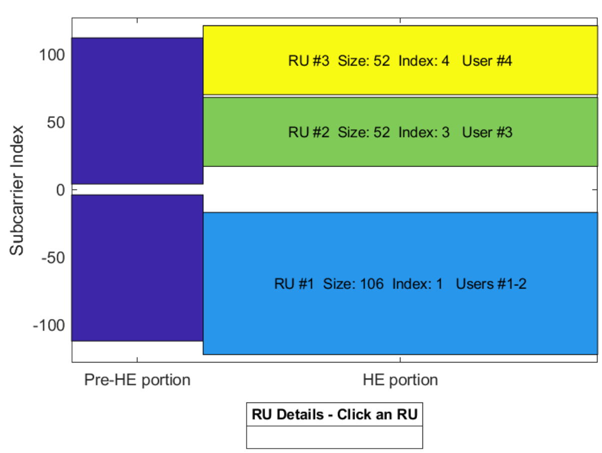

Figure 11. 20MHz, 3 RUs (106, 52, 52)

Let us assume there is downlink MU transmission with a single basic station (BBS) in 50 x 50 office area that has central frequency of 5GHz. The wireless channel can be modeled by WINNER II channel module in MATLAB.

The scenario that was chosen in our simulation scenario is an indoor office (A1) with the parameter "non-line-of-sight (NLOS)". For each simulation scenario, we keep the area of the AP fixed and make a wide range of geographies by arbitrarily distributing the clients. We then report the average value of the sum rate under both the pure OFDMA and the OFDMA with our regression model.
We will appley multiple simulation scenarios:

- Scenario 1: The BBS consists of: One AP with 4 antennas $(N_T = 4)$, 7 users with 1 antenna $(N_R = 1)$, 20MHz bandwidth (L = 4). The result showing in the Figure 12.
- Scenario 2: The BBS consists of: One AP with 4 antennas $(N_T = 4)$, 30 users with 1 antenna $(N_R = 1)$, 40MHz bandwidth $(L = 5)$. The result showing in the Figure 13.
- Scenario 3: The BBS consists of: One AP with 4 antennas $(N_T = 4)$, N users with 1 antenna $(N_R = 1)$, 40MHz bandwidth $(L = 5)$. The result showing in the Figure 14.
- Scenario 4: The BBS consists of: One AP with 1 antenna $(N_T = 1)$, 30 users with 1 antenna $(N_R = 1)$, 40MHz bandwidth $(L = 5)$. The result showing in the Figure 15.

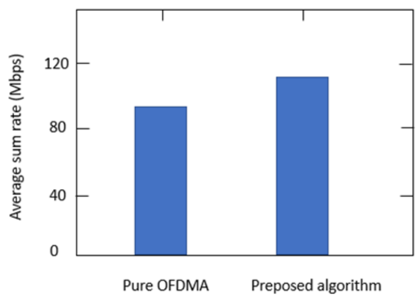

Figure 11. The result of Scenario 1

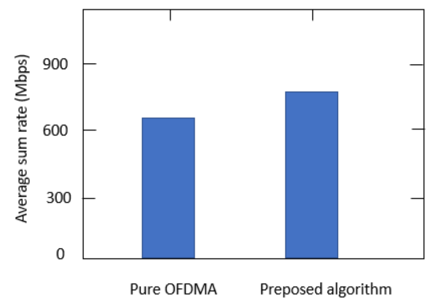

Figure 12. The result of Scenario 2

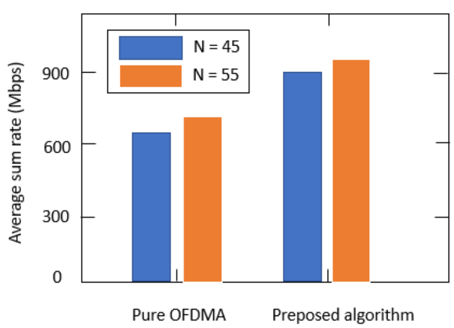

Figure 13. The result of Scenario 3

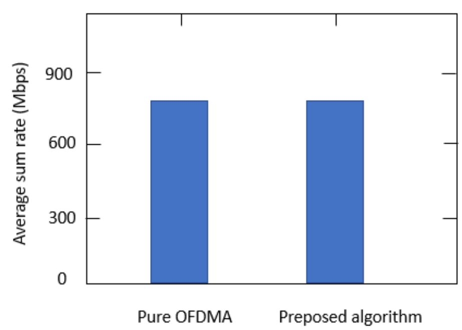

Figure 14. The result of Scenario 4

As can be seen from the figures of all scenarios, the sum rate of our proposed algorithm is higher than pure OFDMA, which is to be expected since it reduces the overhead in the network. In the pure OFDMA scheduling algorithm, we obtain CSI from all users connected to the Ap (all antennas). However, with our proposed algorithm, we obtain the CSI between the users and half of the antennas from AP, and then we predict the rest from CSI from the old algorithm as we described earlier.

Table 2. Simulation result table

Scenarios	Average sum rate of 802.11ax without ML (Mbps)	Average sum rate of 802.11ax with ML (Mbps)
Scenario 1	90.25 Mbps	117.29 Mbps
Scenario 2	620.12 Mbps	820.87 Mbps
Scenario 3 (N = 45, N = 55)	670.15 Mbps, 712.20 Mbps	890.01 Mbps, 928.98 Mbps.
Scenario 4	802.58 Mbps	802.58 Mbps

In scenario 3, we found that the sum rate increased as N increased, so the result of our proposed algorithm also increased. In scenario 4, we have only one antenna on AP, so the average sum rate has the same value in the OFDMA-only scheduling algorithm and our proposed algorithm, because our proposed algorithm uses the number of antennas on the router to reduce network congestion. The average sum rate has increased by 22% to 30% by using our proposed algorithm. This is great to get a faster data score in a Winless network, while there is no standard algorithm for scheduling and resource allocation in 802.11ax (Wi-Fi 6) yet.

6. Conclusion

In this work, we applied a ML method with a previous 802.11ax scheduling algorithm to find a new scheduling algorithm in the 802.11ax standard. First, we divided the antennas of AP into two subsets and then used CSI for one of them as input to the regression model. Using this model, we were able to predict CSI for the second subset. We then applied an algorithm for 802.11ax scheduling and an algorithm for user selection for RUs with more than 106 subcarriers. The goal of the 802.11ax standard is to make Wi-Fi more efficient and faster than the old versions. We were able to increase the average sum performance between 25% and 30% by adding ML to a prioritised algorithm. Detailed simulations comparing the performance of the algorithms show that our practical methods perform very well in all scenarios studied.

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