2011 IEEE 17th International Conference on Parallel and Distributed Systems

Attachment Learning for Multi-Channel Allocation in Distributed OFDMA Networks

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***Abstract*—Wireless technologies have gained tremendous popularity in recent years, resulting in a dense deployment of wireless devices. Therefore, it is desired to provide multiple concurrent transmissions by dividing a broadband channel into separate subchannels. This fine-grained channel access method calls for efficient channel allocation mechanisms, especially in distributed networks. However, most of the current multichannel access methods rely on costy coordination, which significantly degrade their performance. Motivated by this, we propose a cross layer design called Attachment Learning (AT-learning) in distributed OFDMA (Orthogonal Frequency Division Multiple Access) based networks. AT-learning utilizes jamming technique to attach identifier signals on data traffic, where the identifier signals can help mobile stations to learn allocation strategy by themselves. After the learning stage, mobile stations can achieve a TDMA-like performance, where stations can know when exactly to transmit on which channel without further collisions. We conduct comprehensive simulations and the results show that AT-learning can improve the throughput by up to 300% compared with traditional multichannel access method which asks mobile stations to randomly choose channels without learning.**

I. Introduction

Wireless technologies received an explosive growth over the last two decades. Accordingly, wireless devices have been deployed much denser, resulting in a crowded usage of wireless resource. It is desired to divide current frequency band into smaller channels and let more than one users to share a given frequency band. Orthogonal Frequency Division Multiplexing (OFDM) has been considered to be a promising technique of this paradigm, which is capable of providing multi-user diversity gain and combating inter-symbol interference.

Multichannel environments such as OFDM call for efficient channel allocation protocols. In centralized networks, channel allocation is designated by certain authorities (e.g. Access Points (AP) or Base Station (BS)), thus can achieve desired utilization of the available channel capacity. While in distributed networks, since there are no such authorities, channel allocation simply relies on coordination among stations (cooperative) or history knowledge of themselves (non-cooperative). Recently, a lot of research focused on developing distributed multichannel allocation protocols based on Game Theory. The aim of such schemes is to achieve Nash Equlibium (NE) of multichannel allocation game, that is, to achieve the best payoff for all stations in this game. Mahonen et al. [1] propose a simple non-cooperative scheme for multichannel allocation based on Minority Game, where stations maintain access strategy for each channel based on their transmission history. However, with limited information of other stations' strategies, their approach does not have desired NE, and fairness among stations can not be ensured. Gao et al. [2] formalize multichannel allocation in multi-hop networks as a Cooperative Game. They do achieve good NE, yet have to consume certain resource for coordination.

Therefore, a non-cooperative scheme with efficient NE and ensured fairness is desired for multichannel allocation game. Specifically, without coordination, stations are better to learn an access strategy by themselves. To achieve this goal, we propose a Attachment Learning (AT-learning) scheme based on Correlated Equilibrium (CE). The basic idea of CE is to assume a correlation device for all users. Each user chooses its action according to the observation of the value from that correlation device. However, it is non-trivial to implement AT-learning in distributed networks. We encounter the following challenges: Firstly, the coordination device is not available in distributed networks. We need to find an alternative which serves the same purpose. Secondly, we need to design a complete MAC protocol which fully utilizes observed PHY layer information for multichannel allocation.

To address these challenges, AT-learning is positioned as a cross layer design. Specifically, Jamming Detection and Interference Cancellation techniques [21] are utilized as the essential factors in our PHY layer design. By exploring channel redundancy of modulation schemes, for senders who are about to transmit, we are able to let them attach special designed identifiers on their own data packets, and choose one channel to transmit these two types of signals simultaneously. These identifier signals are served as the above mentioned coordination signal. By implementing a secondary radio for each station, they can overhear all identifiers on all subchannels and treat them as a coordination signal vector. Using this attachment transmission, we can self generate a coordination device without further consuming any channel resource. At each receiver side, it can use cancellation technique to remove attached identifiers and recover the original data packets. One possible question might be that whether we are always be able to find such redundancy for attachment transmission. Since the state of art rate adaptation can not fully unitized the whole channel capacity, we argue that data packets are always

1521-9097/11 $26.00 © 2011 IEEE
DOI 10.1109/ICPADS.2011.30

capable of carrying small amount of attachment transmissions.

After gathering coordination signal from PHY layer, we propose a corresponding MAC layer protocol, which help stations within the same collision domain learn an efficient allocation strategy based on each value of the observed coordination signal. Specifically, channels are slotted into transmission rounds. Each station maintains a strategy table that maps each coordination signal to an available subchannel. Before each transmission slot, stations consult to their strategy tables and make access decisions based on the coordination signal value observed from last transmission slot. If their transmission succeed, they will remain their strategies for that coordination signal value. the strategy tables have to be adapted. We argue that this learning based MAC protocol can achieve CE of multichannel allocation. It can also guarantee fairness among stations (will be demonstrated in Sec III).

To summarize, the paper makes the following contributions:

- We propose AT-learning, a cross layer design that based on attachment transmission to provide control information in distributed networks. To the best of our knowledge, it is the first of its kind in the literature to self-attach control information on data packets to achieve cooperation without coordinating.
- We propose a complete MAC solution based on coordination signal learning for multichannel allocation, which can achieve Correlated Equilibrium and converge to TDMA-like performance.
- We theoretically analyze the feasibility of attachment transmission in PHY layer and attachment learning in MAC layer. Extensive simulations verify the effectiveness of our design.

The rest of the paper is organized as follows: Section II provide the preliminary of OFDMA-base system. Learning based allocation scheme is described in Section III, with problem formulation and algorithm analysis. Section IV gives the detailed PHY and MAC layer protocol design of Attachment learning system. System parameters are then analyzed in Section V as design principle. In Section VI, we use Python to evaluate the performance of our design. Relative works are then given in Section VII. We conclude the paper in Section VIII.

II. OFDM/OFDMA Preliminary

In this section, we introduce the background of OFDM/OFDMA based system. It is known that OFDM has developed into a promising technique for multi-carrier transmissions, embraced by many standards to enhance future wireless communications dramatically , including Digital audio and video broadcasting (DAB and DVB), Wireless LANs(WLANs), Wi-Max [3] and 3GPP Long Term Evolution (LTE) [4]. OFDM transforms a frequency-selective wide-band channel into a group of non-selective narrow-band channels named subcarriers, which makes it robust against large delay spreads and cross-talk effect by preserving orthogonality in the frequency domain. On transmitter side, data stream is first divided into several parallel bit streams. Each of these

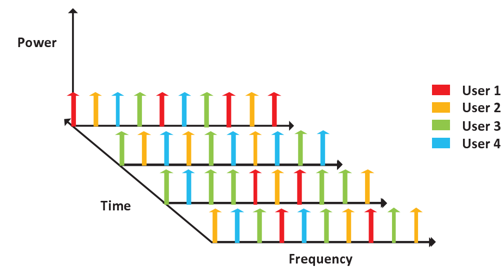

Fig. 1: OFDMA Framework

bit streams is modulated onto individual subcarriers. After performing Inverse Fast Fourier Transform (IFFT), frequency domain bit streams can be converted to corresponding time domain samples. A copy of OFDM symbol's tailing samples called cyclic prefix (CP) is filled in empty guard space to mitigate the effect of dispersive channel distortion. Finally, the parallel to serial block with CP creates the OFDM signal by sequentially outputting the time domain samples to air. The receiver performs the inverse of the transmitter. At the beginning, the OFDM data are split from a serial stream into parallel sets. Then Fast Fourier Transform (FFT) converts time domain samples back into a frequency domain representation. The magnitudes of the frequency components correspond to original data subject to certain scaling and phase rotations. These scaling and phase rotations are mainly due to channel dispersion. Therefore, channel estimation and equalization is needed to recover the original data from the distorted one.

Orthogonal Frequency-Division Multiple Access (OFDMA) is a multi-user version of OFDM, which allows simultaneous low data rate transmissions from several Mobile Stations (MSs or clients). Signals from MSs are separated in the time and/or frequency domains in OFDMA system. Typically, a burst may consist of several OFDM symbols in an OFDMA. As shown is Fig.1, time is partitioned into fixed length frames. A frame can be of length 2, 2.5, 4, 5, 8, 10, 12.5 or 20 ms, depending on the channel conditions, service requirements, and the duration needed for control information. A frame can consist of separate subframes for downlink and uplink. Allocation per MS is performed in units of time $\times$ frequency called slots. The finest allocation units are the subcarriers and the OFDM symbol period in the frequency and time domain, respectively. Hence, multiple MSs are allocated different slots in the time and frequency domain, i.e., different groups of subcarriers and/or OFDM symbols are used for transmitting the signals to/from multiple users. Each MSs can have its own expected bit-rate and Service Level Agreement (SLA). Therefore, efficient mechanisms are desired to make full use of the radio resources, in terms of achieving maximum throughput and minimizing interferences.

III. Formulation and Algorithm Description

Slot Allocation in OFDMA system for multiple MSs Access can be formulated into a resource allocation game. In this section, we first give a brief introduction to resource allocation game. Then we see how Learning based algorithm is proposed to handle this game.

A. Problem Formulation

In resource allocation game, there are M agents who always have some data to transmit. And there are S channels over which they can transmit. In many cases, we have more agents than channels, i.e., $S \leq M$. Therefore, if there are more than one agent attempting to transmit over the same channel, collision is inevitable and none of these transmissions would be successful. In distributed systems, agents are independent from each other. It is extremely difficult for them to achieve correlated equilibrium of allocated resource without coordination. Learning based algorithm is an optimal solution for this type of game, which can converge to a correlated equilibrium in polynomial number of steps. Moreover, fairness can be guarantee among all participant agents. In Learning based algorithm, a randomly chosen integer is adopted as a"stupid" coordination signal. This coordination signal is assumed to exist independently from channel conditions and can be observed by every agent from time to time. Moreover, the channel is slotted and each access from an agent gains one exclusive slot for its transmission. The "smart" agents learn which action they should use for each value of the coordination signal. Specifically, each agent maintains an access strategy table and each coordination signal is mapped to a single channel. Agents observe the common coordination signal before each round of the game and decide which channel they will use in this round. According to the outcome of its transmission (succeed or failure), they will decide whether to change their strategies or not. In the next subsection, we will show the detailed operations of this learning-based algorithm.

B. Algorithm Description

Consider a set $I = \{1, \dots, M\}$ of agents, with a set $S = \{1^i, \dots, M^i\}$ of channels. For each set S^i, time is divided into even slots. The coordination signal has signal space of $C = \{1, \dots, C\}$ and its values remain stable at the beginning of each time slot. Agent i stores an Access Strategy table $f_i : C \rightarrow S \cup \{0\}$. This table simply maps each coordination signal into an exclusive channel or zero to indicate the action for each agent in every time slot. Specifically, for an observed coordination signal C_t in time slot t, agent i has the access authority to channel $f_i(C_t)$ if $f_i(C_t) > 0$. Otherwise, for $f_i(C_t) = 0$, it should defer transmission for time slot t.

Initially, for each coordination signal $c \in C$, agents uniformly distribute each channel from S randomly in their access strategy table. Therefore, each agent has equal chance to access each channel. When transmission starts, agents adapt their strategy according to the following principles.

1) At time slot t, if $f_i(C_t) > 0$, agent i tries to transmit over channel $f_i(C_t)$. Otherwise, if $f_i(C_t) = 0$, agent defers its transmission in this time slot and randomly chooses a channel $m_i(t) \in C$ to monitor for activity.
2) After each transmission round, agent i observes the outcome of its choice:
   - If transmission has been conducted over one channel, it checks whether the transmission was successful. If the transmission was successful, it keeps strategy unchanged for coordination signal C_i. Otherwise if the transmission failed, it assumes collision happened and sets $f_i(C_t)$ with probability p.
   - If transmission has not been conducted during this time slot, it checks whether there was a transmission on channel $m_i(t)$ it monitored. If that channel was free, it sets $f_i(C_t) = m_i(t)$. Otherwise it remains its strategy unchanged.

As shown in [12], this learning-based algorithm is proved to be feasible and reliable. On one hand, this algorithm converges in expected polynomial time to an efficient correlated equilibrium of resource allocation game, which means that it only takes polynomial steps to achieve a stable resource allocation. On the other hand, this algorithm can ensure fairness among agents after converging to an efficient correlated equilibrium, which means that when the resource allocation maintains stable, all the agents can be ensured equal chance to access all the channels. Therefore, this learning-based algorithm is guaranteed to be reliable for resource allocation.

IV. Attachment Learning Design

In this section, we will provide the design of Attachment Learning for multichannel allocation. AT-learning is a cross-layer design that implements learning based algorithm for multichannel allocation in OFDMA-based system. Firstly, an overview of AT-learning is given along with the design challenges. Detailed modules of AT-learning are then presented to see how we address these challenges. There are also some points related to AT-learning design that need to be discussed at the end of this section.

A. Protocol Overview

Learning based algorithm that achieved CE gives us an insight to the design of multiple subchannel allocation in OFDMA-based systems. However, it holds several limitations when bringing it into practical distributed networks.

- First, it is non-trivial to provide a common coordination signal for all nodes within the same collision domain. Simple noise on some frequencies as the algorithm suggested is not feasible due to the uncertainty of the wireless channel. We need to find a reliable and feasible way to provide such coordination signals.
- Second, the observation stage of coordination signal before each transmission time slot is rather expensive, we should find cost-efficient way instead.
- Last, in multichannel scenario, sender and receiver have to negotiate before each transmission, which makes it much more complex to implement learning strategy.

To address these challenges, we proposed a attachment transmission based coordination signal in distributed OFDMA-based networks. This coordination signal is an S dimensional vector, where S is the number of subchannels. Each component of vector $\vec{C_t}$ is a narrow-band signal attached on data

Fig. 2: Illustrated example of attached control messages

symbols in each subchannels. As illustrate in Fig.3, channel is divided into 3 subchannels. At time t_1, the attached signal on each subchannel is 2,3,and 1. Therefore the coordination signal $\vec{C_{t_1}}$ is $\{2, 3, 1\}$. A second radio is adopted for each node to listen on all the subchannels for coordination signal. Therefore, all the nodes within the same collision domain can observe same coordination signal from time to time. Also, since subchannels are slotted, node contends for one subchannel in each time slot. In this paper we only consider single-cell OFDMA-based system. Multiple collision domain raises other problems and thus is remained as future works. As previously shown, when an optimization problem is deployed in an OFDMA system, time considerations are crucial. Therefore, we assume that problems are handled in a framework of frames.

B. PYH Layer Protocol

The foundation of coordination signal vector is to modulate attached information into narrow-band jamming signals [18] and attaches them on data symbols. This Self Jamming technique allows control messages and data traffic to be transmitted simultaneously, and thus fully utilizes the whole bandwidth. When implementing Self Jamming technique, there are two tasks need to be concerned. One is jamming generation and detection, and the other is jamming cancellation and data recovery.

For the former task, in order to avoid interference with each other, each jamming signal should have a bandwidth narrow enough to be included into a single subcarrier even with frequency offset. As a payoff, the capacity of attached control message is small. However, this capacity will be acceptable since control messages can be compressed simple and efficient. Specifically, physical layer signaling with Binary Amplitude Modulation (BAM) is applied in Self Jamming technique. One jamming signal on a particular subcarrier can represent certain information (will be demonstrated later). To detect a jamming signal on a particular subcarrier, we adopt a simple but efficient scheme based on energy detection. According to energy distribution, high throughput transmissions and white noise spread their energy over the spectrum, while narrow-band jamming signal has relatively high energy levels and kind of bursty feature. Therefore, when relatively high level energy is detected on a particular subcarrier, we can assume the presence of a jamming signal. After detecting jamming signal

TABLE I: An illustrated example of strategy table of station i

C_t	1	2	$\cdots$	$C-1$	C
$f_i(C_t)$	S_2	0	$\cdots$	S_1	S_3

on each subcarrier, the receiver can obtain corresponding control messages.

For the latter task, as row signals combing jamming signals and data packets are not directly decodable at receiver side, interference cancellation technique has to be leveraged on subcarriers who carry self-jamming signals. In OFDM based WALNs, channel estimation is performed by transmitting training sequence at the beginning of each transmission packet to obtain the channel state information (CSI) [14]. Since there exists correlation between subcarriers in the frequency domain, CSI of a particular subcarrier can be interpolated with adjacent ones. Therefore, it is feasible to vacate a few of subcarriers [15]. We call these subcarriers clean since ideally there is no signal except noise detected at the receiver side. Taking advantage of these clean subcarriers, we can record each jamming signal in training sequence for the purpose of jamming cancelation and data recovery in subsequent payload data packet. Specifically, the received signal with self-jamming on clean subcarriers of a training sequence can be expressed as:

$$y^{''}\left[t\right] = y_B\left[t\right] + w\left[t\right] \tag{1}$$

Accordingly, the received signal in subsequent data symbol with both data and self-jamming signals can be further expressed as:

$$y^{'}\left[t\right] = y_{\mathrm{A}}\left[t\right] + y_B\left[t\right] + w\left[t\right] \tag{2}$$

where $y_B\left[t\right] = H \times B[t]$ and $y_A\left[t\right] = H \times A[t]$ are jamming and data signals respectively after traversing channels to the receiver. H refers to the corresponding channel impulse response which can be calculated using training sequence and $w[n]$ refers to a random complex noise. Therefore, the original data signal can be recovered by canceling the jamming signal from the received signal in data symbol, that is:

$$X_A = \frac{y_i^{'}\left[t\right] - y_i^{''}\left[t\right]}{H} \tag{3}$$

Fig.2 illustrates self-jamming technique in time/frequency domain. Training sequence carries the recording jamming signals for cancelation and subsequent data packet carries the actually coordination signals. Specifically, coordination signal $\vec{C}$ is generated as following: Subchannels have equal number of subcarriers for transmission, denoted as r. Subcarriers grouped in one subchannel have consecutive values, from 1 to s. At the beginning of each time slot, the node who has data to transmit randomly picks up a subcarrier from its subchannel and attaches a "1" on every data symbol of this subcarrier. This repeating attachment manner ensures that other nodes can observe this signal even they do not synchronize well. Then each subchannel constitutes one value as a component of coordination signal vector $\vec{C}$. Using the second radio to observe all the values across the whole channel, nodes can

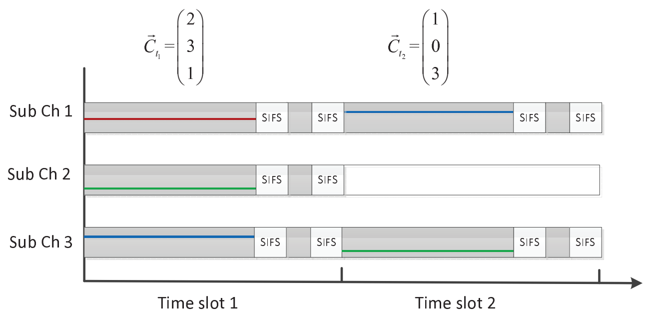

Fig. 3: Multiple transmissions along with attached signals in OFDMA-based systems

obtain coordination signal vector $\vec{C}$ at current time slot, and use this vector to make channel access decision in the next time slot. Fig.3 shows a simple example of generating coordination signal vector $\vec{C}$. Channel is divided into 3 subchannels, each with 5 subcarriers. At time slot t_2, the node transmits on subchannel 1 chooses subcarrier 1(from top down view) and the node transmits on subchannel 3 chooses subcarrier 3. Therefore, $\vec{C_{t_2}}$ is $\{1, 0, 3\}$. 0 means there is no transmission on this subchannel. It is also noted that collision may happen over the same subchannel, thus the attached signal may not be able to recognize. We also assign a special value $(s + 1)$ for this scenario.

C. MAC Layer Protocol

MAC layer protocol is bulit on top of PHY layer information. Complying with the major standard of OFDMA-based distributed networks, there are some necessary assumptions listed below:

1) There are S adjacent subchannels of interest. Each of them has the same number of subcarriers r.
2) Time is divided into even time slots. Each time slot t is used for one transmission round, including data packet and ACK feedback.
3) Nodes get implicitly synchronized when the channel becomes idle, as used in [16]. They all transmit during one time slot.
4) Each node equipped with two half duplex antennas, one is for data transmission and the other is for coordination signal sensing.

Each node maintains an on-line strategy table, which stores the mappings from coordination signal space to available channel space. Since we have S subchannels and each of them with r subcarriers, the coordination signal space is r^S. We can further modify this space by balancing the number of subchannels and subcarriers. Initially a strategy table is constructed by randomly distributing each available subchannel across the whole coordination signal space. Table I depicts an example for a particular node to initialize its strategy table. We can see that subchannels are mapped stochastically to each coordination signal. This randomness ensures that nodes have equal chance to access channel across all available coordination signals.

TABLE II: Notations for BER calculation

k/n	number of information/coded bits in convolutional code
d/d_{free}	hamming distance/free hamming distance of the convolutional code
B_d	total number of information bit ones on all weight d paths
P_d	probability of selecting a code word that is hamming distance d from the correct word

Nodes access subchannels according to coordination signal observed in the previous time slot. Specifically, at the beginning of slot $(t+1)$, it checks $f_i\left(\vec{C_t}\right)$ for decision, where $\vec{C_t}$ is gathered in time slot t. To start transmission at time slot 1, since there is no transmission before, no coordination signal is at hand. Nodes simply treat $\vec{C_0}$ as 0. When transmissions are being conducted, coordination signal is attached on data packets, as illustrated in Fig.3. All the nodes sense the component of coordination signal $\vec{C_{t_1}}$ and store it for the use of channel access decision in next time slot t_2. Also, nodes that do not transmit just keep in receiving mode. Since antenna can receive all the signals across the whole bandwidth, sender-receiver negotiation is evitable. After each transmission, senders adapt their strategy tables according to collision deduced from ACK from their receivers. If no ACK is received, collision is assumed to happen. Sender sets its mapping from $f_i\left(\vec{C_t}\right)$ to 0. Otherwise if ACK is received, transmission succeeds and sender remains its mapping unchanged for $\vec{C_{t_1}}$. Meanwhile, other nodes who intend to transmit but do not actually conduct transmission randomly choose one subchannel S_j to monitor. If the subchannel is free, they set their mapping $\vec{C_{t_1}}$ to S_j.

V. Design Principle

In this section, we analyze the design principles that influence system performance. The main issue is to find out the appropriate signal strength of attached signal on each subcarrier, so that attached signal can be reliably detected along with data packet being safely recovered. Our design follows two principles: on one hand, attached signal cannot be too much stronger to corrupt the original data packets at receiver side; on the other hand, it also can not be too weak for detection. Since when there are multiple concurrent transmissions within the same collision domain, data packets across whole channel superpose at intended sender side, making it crucial for attached signal detection in different subcarriers. Therefore, the design of attached signal strength strikes a tradeoff between these two principles. At the end, a key parameter SIRR, which is the energy radio of data packet to attached signal at the input of the receiver, will be derived for different channel conditions.

A. Principle 1

At receiver side, its Signal to Interference Ratio (SIRR) can be expressed as ${E_b}/{N_a}$, where E_b and N_a are power spectral density of OFDM symbol and Attached signal respectively. To find out an appropriate Signal to Interference Ratio of Receiver that guarantees Attachment harmless to original data packets at receiver side, we use Packet Reception Rate (PRR) to evaluate the quality of data transmission with attachment signals. PRR has a direct connection with Bit Error Rate (BER), which is decided by the encoding/decoding scheme adopted by a communication system. We quantify the relationship between PRR and BER in Fig.4. Normally, OFDM system applies convolutional encoder as channel coding scheme and Viterbi hard decision decoder as channel decoding scheme, then we have an upper bound P_b on BER defined as following:

$$P_b = \frac{1}{k} \sum_{d=d_{free}}^{d_{free}+4} B_d P_d \tag{4}$$

Table II lists the notations for calculating P_b. Specifically, P_d is given by:

$$P_d = \sum_{i=\frac{d+1}{2}}^{d} \left(\begin{array}{c} d \\ i \end{array} \right) P^i (1-P)^{d-i} \tag{5}$$

when d is odd, and

$$P_d = \frac{1}{2} \left(\begin{array}{c} d \\ \frac{d}{2} \end{array} \right) P^{\frac{d}{2}} (1-P)^{\frac{d}{2}} + \sum_{i=\frac{d+1}{2}}^{d} \left(\begin{array}{c} d \\ i \end{array} \right) P^i (1-P)^{d-i} \tag{6}$$

when d is even. Specifically, P can be considered as the uncoded probability of bit error in AWGN under attachment effect, with a minor modification to allow for the code rate $r = k/n$. Since OFDM always adopts binary phase shift keying (BPSK) to modulate preamble with convolutional encoding rate $1/2$, we first use BPSK for illustration. Higher Modulation schemes on data packets, such as QPSK and 64QAM will be talked about later. Supposing the bandwidth of OFDM symbol and attachment are W_s and W_a respectively. Each Attached signal increases the noise power spectral density from N_0 to $N_0 + N_a$. Then we obtain the bit error probability with attachment signal for coded OFDM subcarrier as following:

$$P = \frac{\mathrm{W_a}}{\mathrm{W_s}} Q\left(\sqrt{\frac{2rE_b}{\mathrm{N_0} + \mathrm{N_a}\mathrm{W_s}/\mathrm{W_a}}}\right) + (1 - \frac{\mathrm{W_a}}{\mathrm{W_s}}) Q\left(\sqrt{\frac{2rE_b}{\mathrm{N_0}}}\right) \tag{7}$$

We depict Equ. (4) in Fig.4, which shows the relationship between PRR, BER and SNR under different Signal to Interference Ratio of Receiver. It is noted that the typical working range is from $20dB$ to $30dB$ for wireless networks. From the figure we can see that the energy of attachment transmission actually does not influence BER much. That is mainly because we only jam one particular bit every OFDM symbol. Thus at most we have only one bit error. This result ensures the feasibility of AT-learning.

B. Principle 2

As for intender sender, its desired information is not data packet but Attached signal. Therefore, the Signal to Interference Ratio at the Intended Sender side (SIRS) is defined as

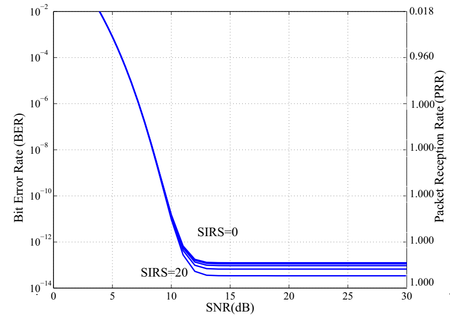

Fig. 4: Relationships between PRR, BER, SNR and SIRR

N_a/E_b. The received signal sample of an intended sender can be represented as:

$$\mathrm{y}(\mathrm{m}) = \sum_{i=1}^{n} \mathrm{h}_i(\mathrm{m}) \left[A_i(\mathrm{m}) + D_i(\mathrm{m}) \right] + \mathrm{w}(\mathrm{m}) \tag{8}$$

where m denotes sample index and $h_i(m)$ denotes impulse response of the ith channel. Without loss of generality, we assume AWGN channel, that is, $h_i(m) = h_0 = 1$. $A_i(m)$ and $D_i(m)$ are attached signal and data packets of the ith channel, with zero-mean and variance of N_a and E_b. $w(m)$ denotes complex Gaussian Noise with zero-mean and variance N_0. According to [20] , the probability of miss an Attached signal when one is present on a certain subcarrier P_{miss} can be expressed as:

$$\begin{aligned} P_{miss}(\lambda) &= Pr(\frac{1}{M} \sum_{m=1}^{M} |\mathrm{y}(\mathrm{m})|^2 < \lambda) \\ &= Q(\tfrac{N_a}{N \times E_b + N_0} + 1 - \tfrac{\lambda}{N \times E_b + N_0}) \sqrt{\frac{M}{2N_a/N \times E_b + N_0{}^{+1}}} \end{aligned} \tag{9}$$

where M is the number of samples and N is the maximum number of neighbors among a node, which means that there are at most N concurrent transmission superposing at a certain intended listener. Therefore, the threshold level for energy detection, λ, should be at least larger than $N \cdot E_b$. We depict Equ. (9) in Fig.4 to see the probability of miss detection P_{miss} under different SNR and Signal to Interference Ratio of Sender. Generally, P_{miss} is acceptable in wireless typical working range, with values below 10^{-10}. Therefore, we can conclude that the signal strength of attachment has not to be too lager than data symbol. This condition can ensure the performance of data packets and also guarantee the performance of attachment detection.

In next section, we will investigate the performance of AT-learning using extensive simulations.

VI. Performance Evaluation

In this section, we present the simulation results for the performance evaluation of our design. The simulations are conducted by Python. We evaluate the system throughput under different conditions comparing with multichannel slotted ALOHA scheme, where stations randomly choose channels

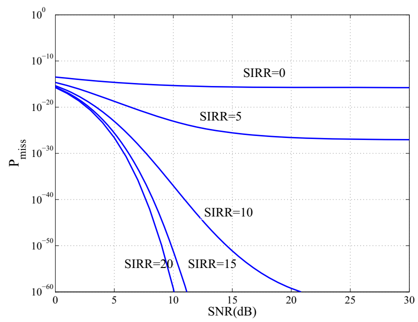

Fig. 5: P_{miss} under different Signal to Interference Ratio of Sender and SNR, N=10

to transmit during each time slot without learning. When stations use multichannel slotted ALOHA as their access algorithm, no carrier sense is performed. Stations transmit on random subchannel without further learning or adaptation in the beginning of each time slot. The reason why we choose multichannel slotted ALOHA instead of multichannel slotted CSMA is that AT-Learning do not need to perform carrier sense to check whether channel is busy or not, therefore it is much like ALOHA to some extend. In the following simulation steps, we use aggregate throughput per station as our metric to evaluate the performance of AT-learning and Multichannel slotted ALOHA. And we consider single-cell OFDMA-based system, which means that stations are all within the same collision domain, contending for totally 10 subchannels. Data transmission rate are 6Mbps and each data packet has length of 1460 bytes. Other useful parameters such as SIFS and DIFS are listed in Table III.

Fig. 6 shows the average throughput of agents using multichannel slotted ALOHA, with different number of stations. Not surprisingly, the throughput is very poor, especially when M=20, which only achieves less than 1.4Mbps per station comparing with data transmission rate of 6Mbps. This is because stations only depends on randomness to avoid transmission collision on each subchannel. Collision happen frequently when number of station grows. Fig. 7 depicts average throughput using AT-Learning. With a transmission rate of 6Mbps, the average throughput of AT-learning can achieve about 4.5Mbps. We notice that as the number of station grows, the aggregated throughput increases for larger coordination signal space. This is because for a lager coordination signal space, stations have more chances to learn and adapt their strategy table for channel access. Therefore, it takes much shorter time for stations to converge to an efficient allocation, and stations can achieve a higher throughout much more quickly. Fig. 8 depicts performance gain of AT-learning over multichannel ALOHA with up to 300%. For different number of stations, AY-learning all performs higher than 4.5Mbps per station, which is very desirable under multichannel environment, comparing with data transmission rate of 6Mbps.This demonstrates that our scheme is efficient to allocate channel for multiple stations, especially for high load networks.

TABLE III: Configuration Parameters

Parameters	**Values**	**Parameters**	**Values**
SIFS	10μs	DIFS	20μs
Symbol time	32μs	Slot time	60μs
Packet length	1460bytes	Basic data rate	6Mbps

VII. Related Works

Researches have been exploiting multiple channel capacity in wireless networks for a long time. A lot of wireless standards are supporting multiple channels for transmission currently, such WiMAX, sensor networks [17] [19] and cognitive radio networks.In sensor networks, a common control channel is usually defined to negotiate channel access for distrusted sensors. Sensors sense the assigned channel, and reports the sensing results to a central station through a specific control channel (e.g., using a 2.4G ISM band [7]). In cognitive radio networks, such control channel is also utilized to assist multi-AP coordination for channel selection [8]. However, the proposed common control channel may not always be available, and coordinations that needs to transmit on such channel from all stations will result in bottleneck.

Adaptive subchannel allocation in [5] is the first work to treat resource allocation as an optimization problem for OFDMA. Then a considerable amount of research based on Game Theory has been conducted for channel allocation problems. The aim of game theoretical approach is to balance users interests, and thus increase the whole system performance. This class of approaches can eliminate common control channel in the above mentioned works. Coordination can also be significantly reduced. The allocation protocol proposed by Mahomen et. al in [1] merely depends on transmission history. Thus it greatly reduces coordination overhead. However, short term transmission history is not a very good interpreter to adapt channel access. Thus it can achieve a throughput better than Multichannel ALOHA. PARK et. al in [10] prove that with enough memory to store transmission history, users can achieve TDMA like performance. However, such memory requirement is too crucial for mobile stations. To achieve efficient multichannel allocation without coordination, Ludek et. al in [12] propose a multi-agent leaning mechanism for distributed users, where a global coordination signal is predefined for learning. They can achieve correlated equilibrium for resource allocation game. However, the coordination signal can not be easily obtained. And sender receiver negotiation is also not considered in their work.

VIII. Conclusion and Future Works

In this paper, we propose a cross layer design called Attachment Learning (AT-learning) for multichannel allocation in distributed networks. First, we analyze the correlated equilibrium of learning based allocation game in terms of convergence time and fairness. Then we propose AT-learning communication system, which is consist of attachment transmission in PHY layer and attachment learning in MAC layer. AT-learning utilizes jamming technique to attach identifier

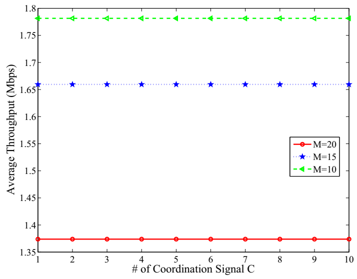

Fig. 6: Performance of Multichannel ALOHA with different number of stations

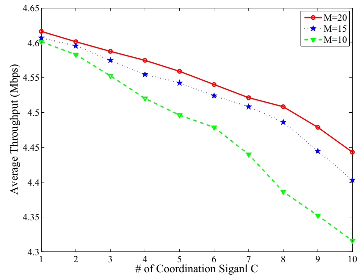

Fig. 7: Performance of AT-Learning with varying signal space C and different number of stations

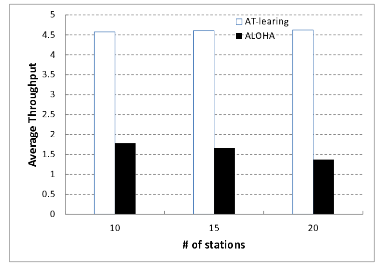

Fig. 8: Performance gain of AT-learning with different number of stations

signals on data traffic. These identifier signals help mobile stations to learn allocation strategy by themselves. We investigate the performance of AT-Learning using Python simulation. Extensive simulation results show that after the learning stage, our scheme can achieve a TDMA-like performance, where stations can know when exactly to transmit on which channel without further collisions. The performance of AT-learning can be improved by up to 300% compared multichannel slotted ALOHA. In next stage, we plan to implement AT-learning on software defined radio (SDR) platform, and test it in multiple scenarios such as multiple collision domain or complex time varying environment.

Acknowledgment

This research is supported in part by HKUST Grant RPC10EG21, and China NSFC Grants (#60933011). Any opinions, findings, and conclusions or recommendations expressed in this paper are those of the author(s) and do not necessarily reflect the views of the sponsor of this research.

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