Attachment-Learning for Multi-Channel Allocation in Distributed OFDMA-Based Networks

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***Abstract*—Wireless technology has become ever more popular in recent years, which results in a higher and higher density of wireless devices. In order to cope with this high density, researchers are proposing the provision of multiple concurrent transmissions by dividing a broadband channel into separate narrow band subchannels. In particular, a fine-grained channel access approach calls for efficient channel allocation mechanisms, especially in distributed networks. However, most of the current multi-channel access methods rely on costly coordination, which significantly degrades network performance. Motivated by this, we propose a cross layer design, termed Attachment Learning (AT-Learning), to achieve multi-channel allocation with low cost and high efficiency in distributed OFDMA based networks. AT-Learning utilizes a jamming and cancellation technique to attach identifier signals to data traffic, without degrading the effective throughput of the original data transmission. These identifier signals help mobile stations learn the allocation strategy by themselves. After the learning stage, mobile stations can achieve a TDMA-like performance, where stations will know exactly when to transmit and on which channel without further collisions. We conduct comprehensive simulations, comparing AT-Learning with a traditional multi-channel access method like Slotted ALOHA. The experimental results demonstrate that AT-Learning can improve the throughput by up to 300% over Slotted ALOHA.**

***Index Terms*—Multi-channel allocation, interference cancellation, game theory, OFDMA.**

I. Introduction

OVER the last two decades, wireless technologies have witnessed explosive growth. Accordingly, wireless devices have been deployed everywhere with high density, resulting in oversubscribed wireless resources. Consequently, it is desirable to divide the current frequency band into smaller channels and let more than one user share a given frequency band. Researchers have examined variations of this paradigm, such as Frequency Division Multiplexing (FDM) and Orthogonal Frequency Division Multiplexing (OFDM). Among these techniques, OFDM is considered to be the most promising choice for the provision of multiple fine-grained channels, since it is able to combat inter-symbol interference and achieving multi-user diversity gain.

Multi-channel environments such as OFDM-based systems call for efficient channel allocation protocols. In distributed networks, there are no authorities(e.g., Access Points) to designate the channel allocation, channel allocation simply relies on coordination among stations (cooperative) or historical knowledge of themselves (non-cooperative). The former retails with a rather high overhead, and the latter has relatively low accuracy, thus neither of them can achieve the desired utilization. Recently, a lot of research is focusing on Game Theory to solve the contention problems in distributed multi-channel environments [1] [2]. They formulize the multi-channel allocation problem as different games, and try to achieve the Nash Equilibrium (NE) of these games. Nash Equilibrium is a solution concept of a game involving two or more players. If each player is making the best decision that he or she can, taking into account the decisions of the others, then they are in Nash Equilibrium. Mahonen et al. [1] propose a simple non-cooperative scheme for multi-channel allocation based on Minority Game, where each station maintains an access strategy for each channel based on transmission history. However, with limited information of other stations'strategies, their approach cannot ensure fairness among stations. Gao et al. [3] formalize multi-channel allocation in multi-hop networks as a Cooperative Game. They do achieve good NE and fairness, yet have to consume certain resource for coordination.

Therefore, we conclude that, for a multi-channel allocation game in distributed networks, we need a non-cooperative scheme with an efficient NE and guaranteed fairness. To be specific, without coordination, stations are better off learning an efficient access strategy by themselves. Here we adopt a Correlated Equilibrium (CE) instead of NE. CE is a probability distribution over the joint strategy profiles of the game [4]. It assumes a correlation device for all the players, which samples the probability distribution and recommends an action for each player. When none of the players can increase its payoff by deviating from the recommended action, the distribution reaches CE. Since the correlation device services as an authority, it can ensure both NE and fairness. However, it is non-trivial to achieve CE in distributed networks: first, the coordination device is not available in distributed networks. An alternative that serves the same purpose is required. Second, we need a complete MAC protocol to fully utilize a correlation signal to achieve CE for multi-channel allocation.

Manuscript received May 4, 2012; revised September 29 and December 10, 2012; accepted December 11, 2012. The associate editor coordinating the review of this paper and approving it for publication was R. Mallik.

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Digital Object Identifier 10.1109/TWC.2013.022013.120627

To address the above challenges, we propose Attachment Learning (AT-Learning), which is a cross layer design that consists of Identifier Attachment in PHY layer and Identifier Learning in MAC layer. The Identifier Attachment is used to provide a coordination signal for MAC layer. Then Identifier Learning guides stations to learning a channel allocation strategy by themselves. These two components together contribute to achieving CE among stations.

In a PHY layer, Jamming Detection and Interference Cancellation are essential techniques [5]. By exploring the channel redundancy of the prevailing modulation schemes, senders are able to inject specially designed jamming signals as identifiers on their own data packets, and transmit these two types of signals simultaneously in the same channel. These identifier signals serve as the above mentioned coordination signals. By implementing a secondary radio for dedicated listening, each station can overhear every identifier across all channels using Jamming Detection. Meanwhile, the receivers manage to remove the attached jamming signals from the received data stream by Interference Cancellation, and can thus successfully recover the original data packets. This attachment transmission helps us self-generate a coordination device without further consuming any channel resources.

After gathering the coordination signal from the PHY layer, we propose an Identifier Learning in the MAC layer for distributed channel allocation without coordination. Identifier Learning helps stations within the same collision domain learn an efficient allocation strategy based on each value of the observed coordination signal. Specifically, time is slotted into transmission rounds and each station maintains a strategy table, mapping each coordination signal to an available channel. Stations consult their strategy tables before each transmission round and make channel access decisions according to the coordination signal observed from previous transmission slot. If a transmission fails, the mapping in the strategy table will be adapted, otherwise it remains unchanged. Through theoretical analysis and simulation we argue that AT-Learning can achieve CE of a multi-channel allocation game and guarantee fairness among stations.

To summarize, the paper makes the following contributions: First, we propose AT-Learning, a cross-layer design based on Identifier Attachment to provide cost-effective 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 coordination. Second, we propose a complete MAC solution based on coordination signal learning for multi-channel allocation, which converges to TDMA-like performance (Correlated Equilibrium). Third, we conduct extensive experiments and simulations to evaluate the effectiveness of Identifier Attachment and the effectiveness of AT-Learning design.

The rest of the paper is organized as follows: Related works are first given in Sec. II. The Learning-based allocation algorithm is described in Sec. III, with problem formulation and algorithm analysis, while Sec. IV gives the detailed PHY and MAC layer design in Attachment-learning systems. In Sec. V, we conduct extensive experiments and simulations to evaluate AT-Learning, and we conclude the paper in Sec. VI.

II. Related Work

Researchers have been exploiting multi-channel capacity in wireless networks for a long time. Many wireless standards are supporting multiple channels for concurrent transmissions, such as WiMAX, sensor networks and cognitive radio networks. Traditional methods for multi-channel allocation can be classified into four categories: dedicated control channel (e.g., DCA [6] and DPC [7]), split phase (e.g., MMAC [8] and MAP [9]), common hopping (e.g., CHMA [10] and CHAT [11], and multiple rendezvous (e.g., SSCH [12]).

Dynamic Channel Assignment (DCA) in [6] is a representation of a dedicated control channel. The overall bandwidth is divided into one common control channel and n data channels. Each node is equipped with a second "control" radio to obtain the access rights. However, under high traffic load, the control channel becomes a bottleneck. Common hopping is a sophisticated approach to solve the channel reservation problem, such as Channel Hoping Multiple Accesses (CHMA) [10]. In CHMA, all nodes hop together and negotiate their transmissions using the same channel. Whenever a sender/receiver pair agrees to transmit, they will stay in that channel and others keep hopping. Common hopping has improved the channel utilization, yet precise synchronization is required among nodes, and switching time for hopping is also a considerable cost. In [12], a multiple rendezvous approach is proposed. Although time is still divided into slots as in common hopping, nodes maintain their own hopping patterns and wait for their intended receivers to transmit. This kind of approach effectively mitigates the congestion on the common control channel, and is actually rudimentary in game theoretical approaches.

Adaptive subchannel allocation in [2] is the first work to treat resource allocation as an optimization problem for OFDMA. Since then, a considerable amount of research based on Game Theory has been conducted for channel allocation problems. The aim is to balance users' interests, and thus the whole system performance can be improved. In [1], the allocation merely depends on transmission history. Thus it greatly reduces the coordination overhead. However, short term transmission history is not a very good interpreter to adapt channel access. So it can only achieve a throughput better than Multichannel ALOHA. In [13], the author prove that with enough memory to store transmission history, users can achieve a TDMA like performance. However, such requirement is too crucial for mobile stations. To achieve efficient multi-channel allocation without coordination, Ludek et. al in [14] propose a multi-agent leaning mechanism for distributed users, where a global coordination signal is predefined for learning. They do achieve Correlated Equilibrium for resource allocation games. However, the coordination signal cannot be easily obtained, and also they do not consider the sender/receiver negotiation.

III. Formulation and Algorithm Description

Slot allocation in OFDMA based systems for multi-MS access can be formulated into a resource allocation game. A particular frequency band in a certain period of time is considered as a slot, and stations simply contend for a slot as the basic transmission unit. In this section, we first give a

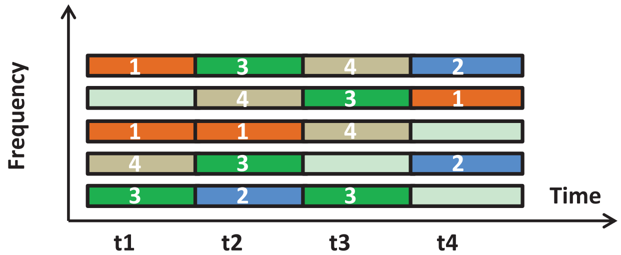

Fig. 1: Coordination signal vector $\vec{C}$.

brief introduction to a resource allocation game as our problem formulation. Then we see how a learning-based algorithm is proposed to handle this resource allocation game.

A. Problem Formulation

We first give the definition of Nash Equilibrium and CE. Let (S, f) be a game with n players. S_i is the strategy set for player i, $S = S_1 \times S_2 \ldots \times S_n$ is the set of strategy profile and $f = (f_1(x), \ldots, f_n(x))$ is the payoff function for $x \in S$. Let x_i be a strategy profile of player i. A strategy profile $x^* \in S$ is a NE if no unilateral deviation in strategy by any single player is profitable for that player. While for CE, there is a "strategy modification" for each player i, which is a function $\phi : S_i \rightarrow S_i$. ϕ tells player i to modify his strategy by playing action $\phi(x_i)$ when instructed to play x_i. Then the strategy profile is a Correlated Equilibrium if no player can improve his profit via a strategy modification. So we utilize the "strategy modification" for resource allocation.

A resource allocation game is defined as a game between M agents and S channels. These agents are the players who always want to obtain transmission access to one of the channels, as to maximize their payoffs. Here we assume $M \geq S$, since in practice, we always encounter the case where there are more agents than channels. Also, channel is slotted. Each access from an agent gains one exclusive slot for its transmission. In distributed systems, agents are independent from each other. It is extremely difficult for them to achieve Correlated Equilibrium of allocated resources without coordination. Learning-based algorithm [14] is an optimal solution for agents to learn a "steady state", with efficient NE and ensured fairness. We propose that a randomly chosen integer exists, which is independent from the channel condition and can be observed by every agent from time to time. This random integer serves as a "stupid" coordination signal, while 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 and then decide which channel they will use in that round. According to the outcomes of their transmissions (success or failure), they will decide whether to change their strategies or not. In the next subsection, we show detailed operations of this learning-based algorithm.

B. Algorithm Description

We define the set $\mathbf{M} = \{1, \ldots, M\}$ as M number of agents, and set $\mathbf{S} = \{1^i, \ldots, S^i\}$ as S number of channels. For each subset $\mathbf{s}^i$ included in set $\mathbf{S}$, time is divided into i number of even slots. The coordination signal has signal space of $\mathbf{C} = \{1, \ldots, C\}$ and each value remains stable at the beginning of each time slot. Each agent stores an Access Strategy Table (AST). AST of agent m is defined as $f_m : \mathbf{C} \rightarrow \mathbf{S} \cup \{0\}$. This table simply maps each coordination signal into an exclusive channel or zero, which exactly indicates the access action in every time slot. Specifically, in time slot t, if the observed coordination signal $f_m(c_t) = 0$, agent m does not have channel access authority and should defer its transmission in time slot t. Otherwise, if $f_m(c_t) > 0$, agent m can have access to channel $f_m(c_t)$ and conduct transmission immediately.

AST is initialized as follows: for each coordination signal $c_0 \in \mathbf{C}$, agent m uniformly chooses one channel from $\mathbf{S}$ and assigns it a coordination signal c_0. This randomized manner can ensure fairness among agents, since they have equal chance to access each channel.

When transmission starts, agents access channels according to their ASTs. Since initially AST is randomized, collisions are unavoidable. Also, some channels might remain vacant. Therefore, agents adapt their strategies in the following two phases: transmission and monitoring.

Transmission: At time slot t, if $f_m(c_t) > 0$, agent m tries to transmit over channel $f_m(c_t)$. After transmission, it observes the outcome of its transmission:

- If the transmission succeeds, agent m keeps mapping channel $f_m(c_t)$ to this coordination signal r_t and AST remains unchanged.
- If the transmission fails, agent m assumes that collision might occur, so it sets $f_m(c_t) = 0$ with probability P_{defer}, which means that it should defer transmission for coordination signal c_t to avoid further collision.

Monitoring: At time slot t, if $f_m(c_t) = 0$, agent m defers its transmission in this time slot. Meanwhile, it chooses a channel $s_i^{'}(t) \in \mathbf{S}$ to monitor the activity.

- If $s_i^{'}(t)$ is free, agent m sets $f_m(c_t) = s_i^{'}(t)$ for coordination signal c_t.
- If there is any transmission on $s_i^{'}(t)$, agent m keeps AST unchanged.

The above learning-based algorithm adopts a constant defer mechanism, where agents defer with the same probability P_{defer} when collision happens. However, when encountering a collision, it is not necessary for all agents to defer with the same probability. So we amend the constant mechanism to get a couple of variants. First, we let agent m defer with the probability $P_{defer} = {|f_m|}/{C}$, where $|f_m|$ refers to the degree of AST (the number of available channels contained in that AST). Then the parties that collided will be more likely to make different access decisions after the AST adaptation. This is called linear defer mechanism, where agents defer according to $|f_m|$. Furthermore, we let the agent m that has the lowest $|f_m|$ maintain the same AST when collision happens, and other parties that collided defer transmission according to $P_{defer} = {|f_m|}/{C}$. This greedy protocol guarantees at least one agent will transmit in the following round. However, it requires agents to obtain other' $|f_m|$s through coordination, and thus it is more complex.

C. Algorithm Analysis

To evaluate the feasibility of the proposed learning-based algorithm, we use two metrics: convergence time to CE and fairness among agents. The convergence time is the estimated number of steps that all agents can achieve to a "steady state", e.g., there are no collisions, and in every channel for every signal value, some agents transmit. While fairness among agents is to see whether agents have equal chances to access all the channels after stability.

1) Convergence time: According to [15], any Nash equilibrium is a Correlated equilibrium. Therefore, we see how learning-based algorithm can converge to a pure-strategy Nash equilibrium of the channel allocation game for every signal value. The calculation is divided into several steps. First, we prove the convergence for simple cases, where $S = 1$ and $C = 1$, along with $S \geq 1$ and $C = 1$. Then we show the general case that $S \geq 1$ and $C \geq 1$. We all assume there are M agents. According to the calculation in [14], we can obtain the following theorems.

Theorem 1. For $S = 1$, $C = 1$, and $0 < P_{defer} < 1$, the expected number of steps to converge to a pure-strategy Nash equilibrium of the resource allocation game is:

$$O\left(\frac{1}{P_{defer}\left(1-P_{defer}\right)}\log M\right)$$

.

Theorem 2. For $S \geq 1$, $C = 1$, and $0 < P_{defer} < 1$, the expected number of steps to converge to a pure-strategy Nash equilibrium of the resource allocation game is:

$$O\left(S\frac{1}{1-P_{defer}}\left[\frac{1}{P_{defer}}\log M + S\right]\right)$$

Theorem 3. For $S \geq 1$, $C \geq 1$, and $0 < P_{defer} < 1$, the expected number of steps to converge to a pure-strategy Nash equilibrium of the resource allocation game for every $c \in C$:

$$O\left(C^2 S\frac{1}{1-P_{defer}}\left[\frac{1}{P_{defer}}\log M + S\right]\right)$$

Therefore, the learning-based algorithm converges in expected polynomial time in the number of agents and channels to reach a steady state (an efficient pure-strateg cases. Specifically, if we take collision into consideration, the convergence time can be further speeded up, e.g. for example, for M agents and S subchannels, the time would be $O(\log S)$.

2) Fairness: Another metric for evaluation is fairness among agents after converging to an efficient CE. We define the number of slots won by an agent i across all time slots as a random variable X_i. This variable follows a binomial distribution, denoted by $X_i \sim B(n,p)$, where $n = C$. Since agents have independent decisions in each time slot, every agent has an equal chance to win. For M agents and S available channels, the probability that an agent can win a given slot is $p = \frac{S}{M}$. For a random variable X_i, we use the *Jain index* [16] to measure fairness:

$$J(X) = \frac{\left(E\left[X\right]\right)^2}{\mathrm{E}\left[X^2\right]} \tag{1}$$

Since $E\left[X\right] = {}^{C\cdot S}/_{M}$, we obtain the following equations:

$$E\left[X^2\right] = \left(C\cdot\frac{S}{M}\right)^2 + C\cdot\frac{S}{M}\cdot\frac{M-S}{M} \tag{2}$$

Therefore, the *Jain index* $J(X)$ can be interpolated as:

$$J\left[X\right] = \frac{S\cdot C}{S\cdot C + \left(M-S\right)} \tag{3}$$

An allocation is considered fair if $J(X)$ is close to 1, which means that all the agents have close possibilities to win equal numbers of slots across all the time slots. For any value of S, it holds that $\lim_{M\to\infty}\frac{M}{S\cdot C} = 0$ if $C = \omega\left({}^{M}/_{S}\right)$ (C is much larger than ${}^{M}/_{S}$, and we assume $M \geq S$ as mentioned above). Then we can obtain $\lim_{M\to\infty} J(X) = 1$, which indicates that if we choose a relatively large C, the resource allocation becomes fairly equitable as M goes to infinity. Therefore, the fairness increases as the signal space of C increases.

IV. Attachment Learning Design

In this section, we provide the design of an Attachment Learning system for multi-channel allocation in OFDMA based systems. First, 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, including PHY layer Identifier Attachment and MAC layer Identifier Learning.

A. Protocol Overview

A Learning-based algorithm that achieves CE gives us an insight to the design of slot allocation in OFDMA based systems. However, it holds several challenges for implementation.

- First, it is non-trivial to provide a common coordination signal for all stations within the same collision domain. The simple noise suggested in [4] is not feasible due to the uncertainty of the wireless channel. A reliable and feasible coordination signal is required.
- Second, since the observation stage for the coordination signal before each transmission time slot is rather expensive, we need to minimize the observation overhead.
- Third, in a multi-channel scenario, the sender and receiver have to negotiate before the transmission, which makes it more complex to implement the learning-based algorithm.

To address these challenges, we proposed an Identifier Attachment based coordination signal in distributed OFDMA based networks. This coordination signal $\vec{C_t}$ is an S dimensional vector, where S is the number of subchannels. Each component of $\vec{C_t}$ c_i is an integer ranging from 1 to r, where r is the number of subcarriers within each subchannel. c_i is derived from the order of the subcarrier with attached signal. As illustrated in Fig. 1, there are totally 5 subchannels, each with 4 subcarriers. At time t_1, subcarrier 1 in subchannel 1 has an attached signal (top down view). Therefore, $c_1 = 1$. In subchannel 2, Since there is no transmission, $c_2 = 0$. Similarly, $c_3 = 1$, $c_4 = 4$ and $c_5 = 3$. So the coordination signal vector $\vec{C_{t_1}}$ is $\{1, 0, 1, 4, 3\}$. A second radio is adopted for each station to listen on all the subchannels for the coordination signal. Therefore, all the stations within the

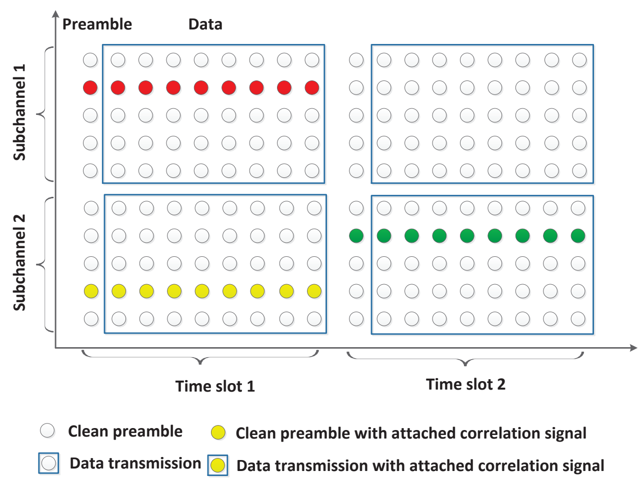

Fig. 2: Illustrated example of how to generate correlation signal with Binary Amplitude Modulation in an attachment manner.

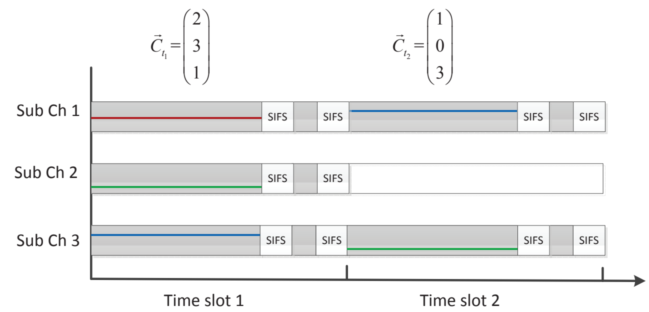

Fig. 3: Multiple transmissions along with attached signals in OFDMA based systems.

same collision domain can observe the same coordination signal vector from time to time. Also, since subchannels are slotted, stations contend for one subchannel in each time slot. In this paper we only consider single-cell OFDMA based systems. The case for multiple collision domains raises other problems and thus remains as a future research. Also, when an optimization problem is deployed in an OFDMA based system, time considerations are crucial. Therefore, we assume that the problems are handled in a framework of frames.

B. PHY Layer Protocol

The foundation of the coordination signal vector is to modulate the attached information into narrow-band jamming signals and attach them on data symbols. This self-jamming technique allows the control message to be transmitted along with data traffic, without occupying additional recourses, and thus fully utilizes the whole bandwidth. When implementing the self-jamming technique, we need to be concerned with two tasks: jamming generation/detection; and jamming cancellation/data recovery.

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

Jamming Cancellation/Data Recovery: Since row signals combing jamming signals and data packets are not directly decodable at the receiver side, interference cancellation techniques have to be leveraged on subcarriers that carry self-jamming signals. In OFDMA based WLANs, channel estimation is performed by transmitting training sequences at the beginning of each transmission packet to obtain the channel state information (CSI) [17]. 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 subcarriers [18]. 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 a training sequence for the purpose of jamming cancelation and data recovery in subsequent payload data packets. The received signal with self-jamming on clean subcarrier of a training sequence is:

$$y^{''}[t] = y_B[t] + w[t] \tag{4}$$

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

$$y^{'}[t] = y_A[t] + y_B[t] + w[t] \tag{5}$$

where $y_B[t] = H \times B[t]$ and $y_A[t] = H \times A[t]$ are jamming and data signals respectively after traversing the channels to the receiver. H refers to the corresponding channel impulse response which can be calculated using a training sequence, and $w[n]$ refers to a random complex noise. Using Equ. 4 and Equ. 5, the original data signal can be recovered by canceling the jamming signal from the received signal in a data symbol, that is:

$$X_A = \frac{y_i^{'}[t] - y_i^{''}[t]}{H} \tag{6}$$

Fig. 2 illustrates a self-jamming technique in time/frequency domain. A clean symbol in training sequence carries the recorded jamming signals for cancelation, and a subsequent data packet carries the actual jamming signals as a coordination signal. The coordination signal $\vec{C}$ is generated as follows: Subchannels have equal numbers of subcarriers for transmission, denoted as r. Subcarriers grouped in one subchannel have different values, from 1 to s. The one with the smallest center frequency represents 1 and the one with the largest center frequency represents s. 0 means there is no transmission on this subchannel. At the beginning of each time slot, the station that is about 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 stations can observe this signal even if 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, stations can obtain a coordination signal vector $\vec{C}$ at current time slot, and use this vector to make a channel access decision in the next time slot. Fig. 2 shows a simple example of generating a coordination signal vector $\vec{C}$. The channel is divided into 2 subchannels, each with 5 subcarriers. At time slot t_1, the station transmitting on subchannel 1 chooses subcarrier 2 (from top down view) and the station transmitting on subchannel 2 chooses subcarrier 4. So $\vec{C_{t_1}}$ is $\{2, 4\}$. Similarly, $\vec{C_{t_2}}$ is $\{4, 0\}$. We notice that when data transmissions collide in one subchannel i, there will be more than one sender transmitting component c_i of $\vec{C}$ in that subchannel. In this case, we use the following rule to determine the value of c_i: If all the senders that collided choose the same subcarrier as c_i, then there will be no confusion since all the stations will observe the same value for c_i; Otherwise, if some of the stations that collided choose different values of c_i, then we always use the smallest value as c_i. This rule guarantees that all stations can observe the same correlation signal even with collision.

PHY Layer Model Analysis: Attachment Coding is feasible and effective only if attachment transmission can be successfully decoded and obtained. Therefore, we use the following model for analysis. The Signal to Interference Ratio at *Attachment* Receiver side (SIRA) is defined as $^{N_a}/_{E_b}$. Then the received signal sample of an intended sender is:

$$\mathrm{y}\left(\mathrm{m}\right) = \sum_{i=1}^{n} \mathrm{h}_i\left(\mathrm{m}\right)\left[A_i\left(\mathrm{m}\right) + D_i(\mathrm{m})\right] + \mathrm{w}(\mathrm{m}) \tag{7}$$

where m is the sample index and $h_i(m)$ is the impulse response of the i^{th} channel. Without loss of generality, we assume an AWGN channel, with $h_i(m) = h_0 = 1$. $A_i(m)$ and $D_i(m)$ are the attached and data signal of the ith channel, with zero-mean and variance of N_a and E_b respectively. $w(m)$ denotes a complex Gaussian Noise with zero-mean and variance of N_0. The probability of missing an *Attachment* when one is present on a certain subcarrier P_{miss} is [19]:

$$P_{miss}(\lambda) = Pr(\frac{1}{M}\sum_{m=1}^{M}\left|\mathrm{y}\left(\mathrm{m}\right)\right|^2 < \lambda) \tag{8}$$

where N is the maximum number of neighbors among a node and M is the number of samples. The threshold level for energy detection, λ, should be at least larger than $N \cdot E_b$, so that the attached signal can be detected through energy detection. Through computation, we found P_{miss} is acceptable in a typical wireless working range(e.g., 10dB to 30dB), with values below 10^{-25}. Therefore, we can say that Attachment Transmission is feasible.

TABLE I: An illustrated example to demonstrate the 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

C. MAC Layer Protocol

The MAC layer protocol is built on top of the PHY layer information. Complying with the major standard of OFDMA based 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 the data packet and ACK feedback. 3) Stations get implicitly synchronized when the channel becomes idle, as stated in [20]. They all transmit during one time slot. 4) Each station is equipped with two half-duplex antennas, one is for data transmission and the other is for coordination signal sensing.

Each station 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 of a particular station initializing its strategy table. We can see that subchannels are mapped stochastically to each coordination signal. This randomness ensures that stations have an equal chance to access channels across all available coordination signals.

Stations access subchannels according to the $\vec{C_t}$ observed in the previous time slot. Specifically, at the beginning of slot $(t+1)$, they check $f_i\left(\vec{C_t}\right)$ for a 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. Stations simply treat $\vec{C_0}$ as 0. As illustrated in Fig. 3, when transmissions are being conducted, components of $\vec{C_t}$ are attached on data packets. All the stations sense $\vec{C_t}$ and store it for the purpose of access decision in the next time slot, whereas stations that do not transmit just keep a receiving mode. Since an antenna can receive all the signals across the whole bandwidth, the sender/receiver negotiation is avoidable. After each transmission, the sender adapts its strategy table if there is no ACK from its receiver (in this case we assume collision will happen), by setting its mapping for $\vec{C_t}$ from $f_i\left(\vec{C_t}\right)$ to 0. Otherwise if ACK is received, the sender keeps its mapping for $\vec{C_t}$ unchanged . Meanwhile, other stations who do not conduct transmission randomly choose one subchannel S_j to monitor. If the subchannel is free, they set their mappings for $\vec{C_t}$ as S_j.

V. Performance Evaluation

In this section, we evaluate the performance of AT-Learning through extensive experiments as well as simulations. First, the PHY layer technique Identifier Attachment, is implemented on a GNU radio testbed consisting of several USRP2 nodes.

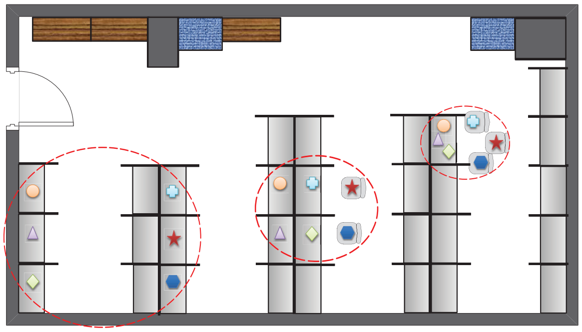

Fig. 4: Experimental environment (3 sets of the six nodes' locations are illustrated as an example).

TABLE II: Configuration Parameters

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

Since the Identifier Attachment is the essential design for the whole system, we need to find out whether it is feasible in a real-time environment. Then we conduct extensive simulations using a self-defined simulator to evaluate the performance of the whole system, including convergence time to reach an efficient allocation, fairness among multiple stations in terms of Jain Index, and system throughput under different conditions. In the following simulations, we compare AT-Learning with a multi-channel Slotted-ALOHA scheme, where stations randomly choose channels to transmit during each time slot without learning. Also, we consider a single-cell OFDMA based system, where stations are all within the same collision domain. We cannot split a channel into too many subchannels to ensure transmission quality, thus the total number of subchannels is set to 10, and each subchannel uses one subcarrier for identifier transmission. The transmission data rate is 6 Mbps and each data packet has a length of 1460 bytes. Other useful parameters are listed in Table II.

A. Performance of Identifier Attachment

The Identifier Attachment is essential to the design of our system, as it provides useful information for higher layers for access decisions. Therefore, its feasibility and reliability will influence the whole system's performance. On one hand, Identifier Attachment is feasible only if the identifiers can be detected and interpreted correctly in the presence of data transmission. On the other hand, Identifier Attachment is reliable only if it does not affect the transmission, detection and decoding of the original data packets. Therefore, we conduct real-time experiments to assess these two aspects. We adopt the Universal Software Radio Peripheral 2 (USRP2) as RF frontend. The testbed consists of 8 USRP2 nodes with RFX2400 daughterboards operating in the 802.11 frequency range. As shown in Fig. 4, the experiments are conducted in our office, which is a typical real world environment with size 5m$\times$8m.

Feasibility of Identifier Attachment: We first evaluate the feasibility of Identifier Attachment in terms of detection accuracy at the receiver side. This is to find out whether a station can correctly detect an identifier and interpret the corresponding component of the correlation signal vector. There are two aspects that influence detection accuracy: Miss Detection Rate (P_{miss}) and False Alarm Rate (P_{false}). P_{miss} is the probability of missing an identifier signal when one is present on a certain subcarrier, and P_{false} is the probability of falsely detecting an identifier signal when it is absent, both these aspects will both result in a decoding failure. Here we use a six-node topology, as shown in Fig. 4, and all nodes are within the same collision domain. Three of them act as senders and the rest of them act as the corresponding receivers. We always let senders have packets to transmit, and when they access certain subchannels, they will transmit both data packets and identifier signals. Each station logs all the identifiers transmitted and sensed during every time slot for calculating P_{miss} and P_{false}. We compute these results under different SNRs of the identifier signal, ranging from 8dB to 20dB. Each run transfers 2500 packets, and for each value of SNR, the experiment is repeated 10 times.

From the experimental results we find that there is almost no P_{false} for any runs, indicating that in real-time experiments, falsely detecting an identifier signal when it is absent rarely happens. Therefore, we only plot the results of P_{miss} in Fig. 5. We can see that when SNR $>$ 13dB, P_{miss} can be controlled within 1%, which results in a detection accuracy of more than 99%. It is noted that the detection algorithm also has an impact on the results. Therefore, the design of a more precise detection algorithm is considered as one of our future research.

Reliability of Identifier Attachment: To evaluate the reliability of Identifier Attachment, we should evaluate the performance of data transmission under the impact of Identifier Attachment. Therefore, we measure the decodability of the data receiver with and without Identifier Attachment. We still use the same topology shown in Fig. 4, all nodes are within the same collision domain. There are totally three node pairs for data transmission. We always let senders have packets to transmit, and when they access certain subchannels, they first transmit both data packets and identifier signals, and then transmit data packets alone using the same access strategy for comparison. We compute the PRR (Packet Reception Rate) at the data receiver side under various SNRs of the data packet, first with, then without identifiers. Each run transfers 2500 packets, and for each value of SNR, the experiment is repeated 10 times.

As depicted in Fig. 6, we plot the PRR of the data receiver with/without Identifier Attachment as a function of the received SNR at the data sender side from 4dB to 20dB. We can see that when the SNR exceed a certain threshold, i.e., 8dB, the PRRs with and without Identifier Attachment are almost the same. We notice that there is a little performance degradation when the SNR is smaller than 8dB. This can be acceptable since the typical working range of a SNR region for 802.11 is 10dB to 30dB [21]. These results verify that the original data transmission can be successfully decoded in the presence of Identifier Attachment.

In the next step, we evaluate the impact of a number of concurrent identifier signals on the decodability of the data receiver. We use a similar setting to evaluate the PRR

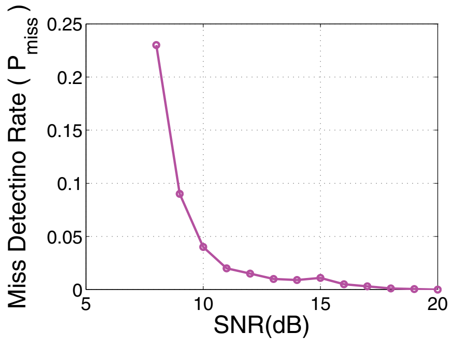

Fig. 5: Miss detection rate of identifier signal under different SNRs.

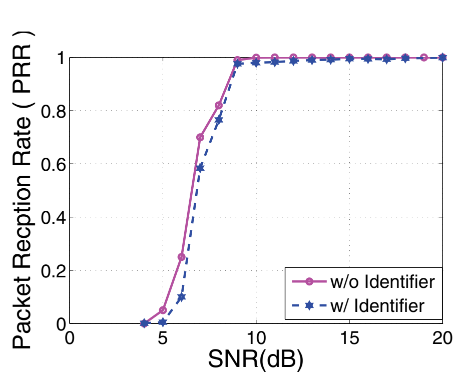

Fig. 6: Decodability of data packet with/without identifier signal under different SNRs.

of the data receiver, but with different numbers of concurrent identifiers varying from 1 to 6. To avoid confusion, we assign fixed values of identifier vectors for each run, such as $\{1,0,0,0,0,0,0,0,0,0\}$ for one identifier signal and $\{1,1,0,0,0,0,0,0,0,0\}$ for the second identifier signals. Thus we can ensure the number of identifier signals concurrently transmitted in the air.

We calculate the Packet Loss Rate (PLR) under different number of identifier signals with SNR 10dB and 15dB. The results show that the performance losses are all under 10^{-2}, even with 6 concurrent identifier signals, which are relatively small. Therefore, we conclude that Identifier Attachment is reliable and harmless to the original data transmission.

B. Performance of Identifier Learning

Since USPR2 has a latency constraint, we can not use it to conduct real-time evaluation of the whole AT-Learning system. Therefore, we implement a self-defined simulator using python to evaluate the performance of our system. The simulator follows the same settings in Table II. The total number of subchannels is still 10, each with 1 subcarrier for identifier transmission. The constant defer mechanism of Identifier Learning is adopted here, where P_{defer} is set to 0.5. We compare AT-Learning with multi-channel Slotted-ALOHA, with different number of stations ranging from 10 to 50. To focus on the performance of the channel utilization, we assume that the network is saturated and the packet reception failure is only caused by the collisions.

Convergence Time: Fig. 7 presents the average number of convergence steps before reaching an efficient allocation ("steady state"). We see that convergence time increases as the coordination signal space C increases. This is quite reasonable and consistent with the analysis in Sec. III-C. Larger coordination signal space requests more steps for convergence, since as the number of coordination signals increases, stations may have to wait a long time for the appearance of a certain coordination signal to transmit. Thus convergence is reached until all the stations have transmitted according to all the coordination signals. It is interesting that it takes the longest time to converge when $M = S$, which is also discussed in [4]. Despite $M = S$, the convergence steps increases as the number of stations increase, mainly because more stations have relatively high probabilities of introducing collisions. Thus they have to adapt strategy tables more frequently, resulting in a longer convergence time. However, the convergence time is around 10^2 even with 10 correlation signals, which is acceptable for the initialization of a network.

Fairness: Fairness is also another important metric to evaluate the feasibility of our scheme. Recalling in Sec. III-C, we deduce that if we choose a relatively large C, $J(X)$ is close to 1 when the number of agents is close to infinity, which theoretically proves that our scheme is fair enough. Since in practice we are not allowed to choose a large value of C as the number of subcarriers is limited, we evaluate fairness using a small value of C to see how At-Learning perform in real world environments. We calculate the average probability of all the stations to access the channel. When $M = S$, this probability approximates 1, which means each agent in every slot has equal chances of transmitting on one channel. As the number of stations increases, fairness decreases, since there will not be enough channels for each station's transmission in every time slot. This reduction can be compensated by increasing the signal space of C, as it exceeds a certain threshold, e.g., $C = 5$, fairness is above 65% even with 40 stations. This is mainly because with more coordination signals, stations can balance their strategies with each other. Taking convergence time and fairness together into consideration, we observe a tradeoff of choosing C. C cannot be too large since convergence time will be too long, nor can it be too small to ensure fairness. Different systems require different Cs. For a network with 10 subchannels and 10 to 30 stations, we consider $C = 6$ according to the simulation results.

Average Throughput: In this step, we evaluate the average throughput of an AT-Learning system comparing with multi-channel Slotted-ALOHA under a different number of stations ranging from 10 to 30, which is a typical size of a contention domain. When stations use multi-channel Slotted-ALOHA as their access scheme, no carrier sense is performed, and they randomly choose subchannels to transmit without learning or adaptation. The reason we do not choose multi-channel Slotted-CSMA is that AT-Learning does not perform carrier sense to check whether the subchannel is busy or not before transmission, it merely relies on a strategy table to determine whether to access the channel or not. Monitoring is only performed when stations do not transmit in a certain time slot. Therefore, it is more like ALOHA to some extent.

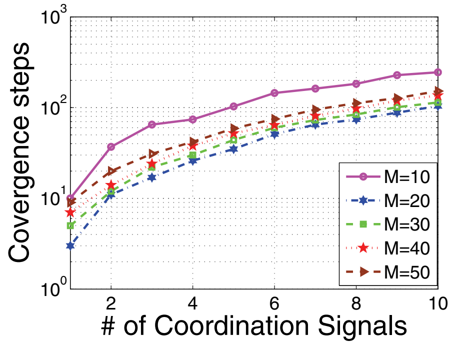

Fig. 7: No. of Steps that stations can reach an efficient allocation.

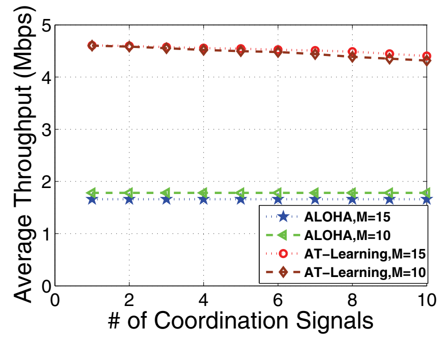

Fig. 8: Performance of AT-Learning and multi-channel Slotted-ALOHA with varying signal space C (M=10, 15).

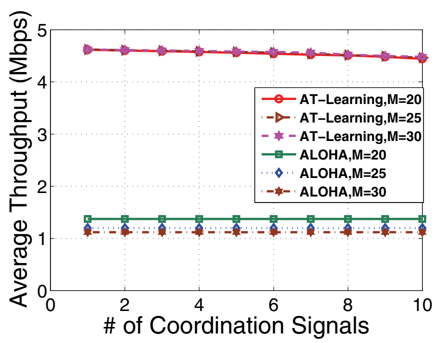

Fig. 9: Performance of AT-Learning and multi-channel Slotted-ALOHA with varying signal space C (M=20, 25,30).

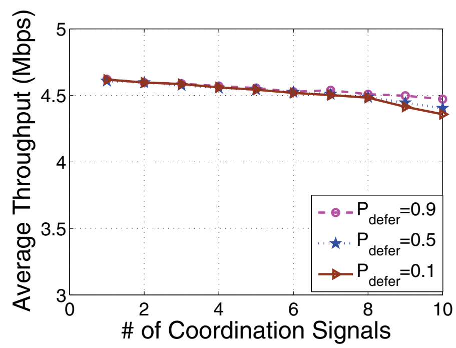

Fig. 10: The impact of defer probability P_{defer} on the performance of AT-Learning (M=15, S=10).

Fig. 8 and Fig. 9 show the average throughput of agents using multi-channel Slotted-ALOHA and AT-Learning after reaching a steady state. Not surprisingly, the throughput of multi-channel Slotted-ALOHA is very poor, especially when $M = 30$, which only achieves less than 1.2 Mbps per station comparing with a data transmission rate of 6 Mbps. This is because stations only depend on randomness to avoid transmission collision on each subchannel. Thus collisions happen frequently when the number of stations increases. On the contrary, the throughput of AT-Learning can achieve about 4.5 Mbps with different numbers of stations. This verifies that AT-Learning can ensure network performance even under high traffic load. It is noted that the average throughput is lower for $M = 10$ than for other M's. This performance deduction is mainly due to miss detection and false alarm of the coordination signal. In such cases, the stations cannot reach an agreement on their strategy tables. Therefore, collision may happen frequently even after convergence. We also study the impact of defer probability P_{defer} on the performance of AT-Learning. From Fig. 10 we can see that the value of P_{defer} has little influence on the average throughput when C is smaller than a threshold, e.g., $C = 7$. When C becomes relatively large, e.g., $C = 10$, the aggregated throughput decreases as P_{defer} decreases. This is mainly because after convergence, a lower defer probability will lead to a higher probability of collision. With a larger value of C, it will cost more time to coverage again, and thus degrade the performance to some extent. Therefore, in such cases, and it is better to set P_{defer} to a larger value (e.g., $P_{defer} = 0.5$) to ensure the overall throughput.

We calculate the performance gain of AT-Learning over a multi-channel Slotted-ALOHA. The gain is up to 300%. For different numbers of stations, AT-Learning performs higher than 4.5 Mbps per station, which is very desirable with a data transmission rate of 6 Mbps. These results demonstrate that our scheme is efficient enough to allocate channels for multiple stations.

VI. Conclusion and Future Works

In this paper, we have proposed a cross-layer design called Attachment Learning (AT-Learning) for multi-channel allocation in distributed networks. First, we analyze the Correlated Equilibrium of learning-based allocation problems in terms of convergence time and fairness. Based on Correlated Equilibrium, we propose an AT-Learning communication system, which utilizes a jamming technique to attach identifier signals on data traffic. These identifier signals help mobile stations to learn allocation strategies by themselves, without occupying the bandwidth of the original data packets. We investigate the performance of AT-Learning using extensive experiments and simulations, and find that after the learning stage, our scheme can achieve a TDMA-like performance, whereby stations can know exactly when to transmit on which channel without further collisions. Performance can be improved by up to

300% compared with a multi-channel ALOHA. In the next stage of our research, we plan to test AT-Learning under scenarios such as multiple collision domains or complex time varying environments, and apply it to other communication systems, such as cognitive radio networks, to handle the spectrum sharing problem among secondary users.

ACKNOWLEDGMENT

This research is supported in part by HKUST Grant RPC10EG21, Guangdong Natural Science Funds for Distinguished Young Scholar (No.S20120011468), China NSFC Grant 61202454, Guangzhou Pearl River New Star Technology Training Project (No.2012J2200081), Guangdong NSF Grant (No.S2012010010427). Kaishun Wu is the corresponding author.

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