Access Point Selection under QoS Requirements in Variable Channel-Width WLANs

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***Abstract*—This work investigates the access point (AP) selection problem in Variable channel-width WLANs (V-WLANs) using an evolutionary game-theoretic approach. A practical utility function is designed for each station in which the QoS requirement and energy consumption are considered. An Evolutionary Stable Strategy (ESS) of the game corresponds to the desired AP selection outcome, which remains stable even if the stations occasionally select inappropriate APs. A distributed learning algorithm based on replicator dynamics is developed to obtain the ESS with only local information. Simulation results verify the convergence and effectiveness of our algorithm.**

***Index Terms*—AP selection, variable channel-width WLANs, evolutionary game.**

I. Introduction

THE variable channel-width technology is recently proposed to improve the performance of WLAN in terms of fairness and capacity [1,2]. In Variable channel-width WLANs (V-WLANs), the total available spectrum is partitioned into several channels with variable widths, and hence channel allocation in V-WLANs is more flexible and efficient than those in traditional WLANs. Although channel allocation in V-WLANs has been investigated in the literature [2][3], the AP selection problem remains open for V-WLANs. The variability of channel-widths of V-WLANs poses two new challenges to AP selection. First, the channel-width of an AP should be taken into account since it affects the bandwidth obtained by associated stations. Second, energy consumption for using a channel may vary depending on the channel width [1]. In this letter, we propose a distributed approach for a desired AP selection outcome. It is noted that the variability of channel-widths provides the network with a tuning capability to satisfy different quality of service (QoS) requirements. And the QoS requirement of each station is therefore considered in this study.

Based on the assumption that stations are completely rational [4], the AP selection problem can be formulated as a non-cooperative game. Here, we relax this assumption and formulate the AP selection problem as an evolutionary game. Evolutionary game is more suitable than traditional non-cooperative game since it can investigate the trajectory of the AP selection progress and is compatible with the bounded rationality of stations [5]. Compared to [5], this letter also investigates how to lead stations to achieve a desired AP selection outcome, i.e., an evolutionary stable strategy (ESS) that can satisfy the QoS requirements. A distributed learning algorithm based on replicator dynamics is proposed, which does not require global information and can achieve a desired AP selection outcome even if some stations occasionally make inappropriate AP selections[1].

II. Problem Formulation

Consider a V-WLAN with M APs and N ($N > M$) stations. Let $\boldsymbol{M} = \{1, 2, \dots, M\}$ and $\boldsymbol{N} = \{1, 2, \dots, N\}$ denote the sets of APs and stations, respectively. The channels with different widths are allocated to the APs. As in [2] and [3], we only consider the non-overlapping channels since empirical measurements in [1] suggest that assigning non-overlapped channels is beneficial. Each station, say i ($i \in \boldsymbol{N}$), has a QoS requirement d_i, i.e., a guaranteed achievable bandwidth.

A station aims to associate with an appropriate AP to satisfy the QoS requirement and maximize its self-interest. Due to the variations in both channel-widths and received signal strengths, it may obtain various bandwidths from the APs, that can be defined as

$$R_{i,j} = \lambda_{i,j} B_j \tag{1}$$

where B_j denotes the channel-width of AP j ($j \in \boldsymbol{M}$) and $\lambda_{i,j}$ is the efficiency factor of bandwidth[2].

To decide whether or not to associate with an AP, a station needs to evaluate the corresponding bandwidth. To do it, a station assumes that it shares the access time equally with the others associated with the same AP [2,3,8,10]. Under saturated traffic, the expected bandwidth of station i associated with AP j can be calculated as

$$T_{i,j}(R_{i,j}, n_j) = o_{i,j} R_{i,j}/(n_j+1) = o_{i,j} \lambda_{i,j} B_j/(n_j+1) \tag{2}$$

where n_j is the number of other stations selecting AP j, and $o_{i,j}$ represents the bandwidth loss factor due to the overhead of PHY/MAC protocols, $0 < o_{i,j} < 1$. In general, $o_{i,j}$ is a non-increasing convex function of n_j, and a non-decreasing concave function of $R_{i,j}$ [6].

A station obtains its bandwidth at the price of energy consumption. Note that most 802.11 protocols (e.g., 802.11 g/a/n) adopt the Orthogonal Frequency Division Multiplexing (OFDM) approach and the channel width is proportional

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[1]The users may make mistakes in AP selection due to their bounded rationality, which is referred to as “inappropriate AP selections”.

[2]Here, we assume that all the stations adopt the most efficient modulation/demodulation and coding schemes (MCSs) to achieve their highest bandwidth efficiencies under the power constraints.

to the number of subcarriers. The transmission power for each OFDM subcarrier can then be assumed to be equal [1]. The cost of energy consumption of station i associated with AP j can be calculated as $\rho_{i,j}B_j$, where $\rho_{i,j}$ is the energy consumption factor, which denotes the power per Hz to sustain the bandwidth efficiency under the power constrains. To characterize the net revenue of a station in AP selection under the QoS requirement, a practical utility function is designed for each station, which is defined as

$$u_{i,j} = \begin{cases} log\frac{o_{i,j}\lambda_{i,j}B_j}{n_j+1} - \rho_{i,j}B_j & if \ \frac{o_{i,j}\lambda_{i,j}B_j}{n_j+1} \geq d_i \\ -\rho_{i,j}B_j & otherwise. \end{cases} \quad (3)$$

The utility function takes two kinds of traffics into account. The first (e.g., voice and video) has a minimum bandwidth requirement, denoted by $d_i, (d_i > 0)$. The second (e.g., web access) requires a best-effort service and has no requirement for bandwidth (i.e., $d_i = 0$). In practice, the rate of change of the utility becomes slower when the bandwidth is already large. Hence, a log function is introduced in our utility function to describe this feature.

III. Game Model

We formulate the AP selection problem as an evolutionary game, in which the station acts as the player, the strategy is denoted by the index of the selected AP, and $u_{i,j}$ is used as the payoff function. In this work, we consider the stations with bounded rationality, who may occasionally make mistakes, i.e. inappropriate AP selections. This behavior is called perturbation, which acts as the invaders (mutations) into the evolution progress and may result in system instability and vast re-association operations. To overcome this shortcoming, an ESS AP selection outcome should be achieved. Compared with the traditional solution concept of Nash equilibrium (NE), ESS is more stable since it is robust against invaders [7].

Let $\theta_{i,j}$ denote the probability of player i adopting strategy j, and $\theta_i = (\theta_{i,1}, \theta_{i,2}, \ldots, \theta_{i,M})$ denote the mixed strategy of player i. We define the strategy profile as $\Theta = (\theta_1, \theta_2, \ldots, \theta_N)$, and then the ESS can be defined as follows:

Definition 1. *The strategy profile Θ^* is an ESS if and only if, for all $\Theta' \neq \Theta^*$*

$$u(\Theta^*, (1-\epsilon)\Theta^* + \epsilon\Theta') > u(\Theta', (1-\epsilon)\Theta^* + \epsilon\Theta') \quad (4)$$

In (4), ϵ is a positive value close to 0, which denotes the fraction of player adopting Θ'. It can be observed that the utility of player adopting ESS (Θ^*) is always higher than that of the invaders (Θ'). From a biological perspective, the invaders, who have lower utilities, will extinct gradually. In our problem, when a station occasionally makes a mistake (i.e., adopting Θ'), lower bandwidth is achieved comparing to that adopting the ESS. Hence, the ESS outcome is preferred so that inappropriate AP selections can be avoided.

Actually, an ESS defined in evolution game theory can be a mixed or pure strategy profile [7]. When a mixed-strategy profile is adopted, the stations keep switching their APs. To avoid frequent re-association operations, the ESS with the form of a pure-strategy profile is desired in practice. As shown in the following proposition, the ESS in our game is always a pure-strategy profile. That is, when the ESS is achieved, every station chooses an AP in a deterministic, non-aleatory manner.

Proposition 1. *No mixed-strategy profile can be an ESS in our AP selection game.*

Proof: When applying replicator dynamics, the ESS is equivalent to the steady state[3] with asymptotically stability [9]. As shown in the utility function, our AP selection game is an asymmetric game since the efficiency factors, energy consumption factors and QoS requirements for the stations are not identical. Besides, mixed-strategy cannot be asymptotically stable in asymmetric games [7]. Therefore, no mixed-strategy profile can be an ESS in our AP selection game. ■

It should be pointed out that an ESS may not exist occasionally in our game. It happens when a station has multiple feasible APs with the same utility value. In this situation, its replicator dynamics will reach a steady state with a mixed-strategy. We therefore make the station select the AP with the highest probability in its mixed-strategy. In this way, no matter whether an ESS exists or not, our AP selection outcome is always pure-strategy, which can avoid frequent re-association operations. The only problem left is how to lead the stations to achieve the ESS.

IV. Distributed Learning Algorithm

As in [7], the ESS can be obtained using the replicator dynamics

$$\dot{\theta}_{i,j} = \theta_{i,j}(\overline{u}_{i,j} - \overline{u}_i), i \in \boldsymbol{N}, j \in \boldsymbol{M} \quad (5)$$

$\dot{\theta}_{i,j}$ is called the rate of strategy adaptation [8], which indicates the rate of change of the probability of strategy j being adopted by player i. The notation $\overline{u}_{i,j}$ represents the average utility of player i adopting the pure-strategy j, and $\overline{u}_i$ is the average utility of player i adopting mixed-strategy with current probability distribution $\theta_{i,j}$. With (3), $\overline{u}_{i,j}$ and $\overline{u}_i$ can be obtained as

$$\begin{aligned} \overline{u}_{i,j} = & \sum_{n=0}^{N_{i,j}-1} [log(\tfrac{o_{i,j}\lambda_{i,j}B_j}{n+1}) - \rho_{i,j}B_j] Pr\{n_j = n\} \\ & - \sum_{n=N_{i,j}}^{N} \rho_{i,j}B_j Pr\{n_j = n\} \end{aligned} \quad (6)$$

$$\overline{u}_i = \sum_{j=1}^{M} \theta_{i,j}\overline{u}_{i,j} \quad (7)$$

where $N_{i,j}$ is the maximum number of stations selecting the same AP as station i under the QoS requirement of station i, and $Pr\{n_j = n\}$ is the probability of that the number of other stations associating with AP j equals to n. We have $N_{i,j} = min(\lfloor o_{i,j}\lambda_{i,j}B_j/d_i \rfloor, N)$ and

$$Pr\{n_j = n\} = \overbrace{\sum_{\substack{l_1=1,\\ l_1 \neq i}}^{N} [\theta_{l_1,j} \cdots \sum_{\substack{l_n > l_{n-1},\\ l_n \neq i}}^{N} [\theta_{l_n,j}}^{n} \prod_{\substack{k=1,\\ k \neq i, l_1 \ldots l_n}}^{N} (1-\theta_{k,j})]] \quad (8)$$

The replicator dynamics reach the steady state when $\dot{\theta}_{i,j} = 0 (i \in \boldsymbol{N}, j \in \boldsymbol{M})$. However, a non-ESS state can also be the

[3] The steady state corresponds to some particular points in the dynamics defined in section IV.

Algorithm 1 LARD

1: Station/player i initializes its average utility values and mixed-strategy;
2: $\overline{u}_{i,j}(0) = 0$, $\overline{u}_i(0) = 0$, $\theta_{i,j}(1) = 1/M, j \in \boldsymbol{M}$
3: **While** stopping criterions 1 and 2 are not met
4: Station i randomly chooses a feasible AP $s_k, s_k \in \boldsymbol{M}$, based on its probability distribution of mixed-strategy $[\theta_{i,1}(k), \theta_{i,2}(k), \ldots, \theta_{i,M}(k)]$
5: **if** $s_k \neq s_{k-1}$ **then**
6: station i switches to s_k;
7: **end if**
8: Station i calculates the utility $\tilde{u}_k$ by (3);
9: Update $\overline{u}_{i,j}(k)$ and $\overline{u}_i(k)$ by (9) and (7);
10: Update the rate of strategy adaption and the mixed-strategy for next iteration by (5) and (10);
11: **if** $\theta_{i,j}(k) < \varepsilon_2, j \in \boldsymbol{M}$ **then**
12: $\theta_{i,j}(k) = \varepsilon_2$; (Perturbation Injection)
13: **end if**
14: Normalize the probabilities to satisfy $\sum_{j=1}^{M} \theta_{i,j}(k) = 1$;
15: **end while**

steady state [7], and thus the stations have to rule out the non-ESS states. We introduce here a procedure called perturbation injection to force the players to jump out of the non-ESS steady states of the game. This method is inspired by the fact that non-ESS steady states will be changed by a small perturbation, while an ESS is robust to such a perturbation [7]. In the perturbation injection procedure, the stations' probabilities selecting their APs are always set to a value higher than a pre-determined threshold. In this way, the non-ESS steady states cannot survive and the achieved state will be an ESS[4]. It should be pointed that the size of perturbations should be small to avoid oscillations among multiple ESSs[5].

Another challenge is the conflict between global information requirement and distributed implementation. As shown in (6) and (7),to calculate $\overline{u}_{i,j}$, each player needs to know the selection probability distribution of all the players, i.e., Θ, which is impractical due to the vast communication overhead and delay [9]. Moreover, the computation complexity of (8) is also unacceptable when the number of stations is large. To overcome these shortcomings, we estimate $\overline{u}_{i,j}$ using reinforcement learning, that is,

$$\overline{u}_{i,j}(k) = \begin{cases} (1-\beta_k)\overline{u}_{i,j}(k-1) + \beta_k \tilde{u}_k & if \;\; j = s_k \\ \overline{u}_{i,j}(k-1) & otherwise. \end{cases} \quad (9)$$

where k is the iteration index and $\beta_k, 0 < \beta_k \leq 1$ is the learning rate. s_k and $\tilde{u}_k$ represents the AP selection and its utility in the k-th iteration, respectively. The initial value of $\overline{u}_{i,j}(k)$ is set as 0. Note that both $\frac{o_{i,j}\lambda_{i,j}B_j}{n_j+1}$ and $\rho_i B_j$ in (3) can be measured locally, and hence global information is not needed. During the learning, the player's mixed-strategy updates based on the replicator dynamics, and the iterative formula can be represented by

$$\theta_{i,j}(k+1) = \theta_{i,j}(k) + \mu\dot{\theta}_{i,j}(k) \quad (10)$$

where $\dot{\theta}_{i,j}(k)$ is the rate of strategy adaptation in the k-th iteration, which can be calculated by (9), (7) and (5). The gain for the change rate is controlled by the parameter μ [8]. According to [9], the discrete-time replicator dynamic system converges asymptotically to a stable point, i.e., an ESS, with a small value of μ, since the ESS is asymptotically stable and hyperbolic in the continuous-time replicator dynamics [7]. Thus, the stations can obtain an ESS with only local information using the proposed reinforcement learning.

According to the above analysis, we propose a distributed algorithm, called learning algorithm based on replicator dynamics (LARD). The algorithm is described in **Algorithm 1**. In our algorithm, the trial and error method is used for stations during the learning. The station chooses its AP based on the probability distribution of the mixed-strategy (lines 4-7 in LARD), and it gets the average utility by (9) and updates its mixed-strategy based on the replicator dynamics (5) (lines 8-10 in LARD). We introduce two stopping criterias here. The first is that every station's probability of selecting a certain AP is higher than $1-\varepsilon_1$ for η_1 consecutive iterations. It indicates that an ESS has been achieved by ruling out the non-ESS steady states through perturbation injection (lines 11-14 in LARD). The second is that the number of iterations reaches the maximum of η_2. This criteria will be activated when no ESS exists.

In practice, an admission control mechanism is valuable since it can reject the stations with an overly strong QoS requirement. With LARD, the admission control mechanism can be implemented as follows. First, LARD is run by all the stations and an ESS outcome is obtained. If the QoS requirement of a station is not satisfied, its utility will be negative. The station will then perform the AP disassociation operation to enhance its utility (to zero). Second, LARD is run by the remaining stations and a desirable ESS outcome, which satisfies all the remaining QoS requirements, will be achieved.

V. Simulation and Discussion

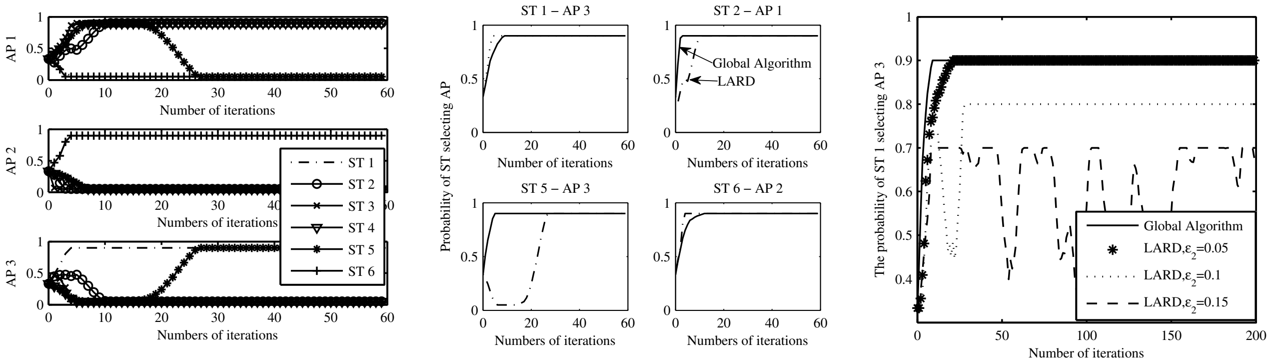
In our simulation, APs and stations (STs) are randomly distributed in an area of 200m×200m. The channel-width for each AP is randomly chosen from $\{5, 10, 20, 40\}$ (MHz) [1], and bandwidth efficiency (R/B) for each Station-AP pair is determined by the propagation model and the signal-interference-and-noise-ratio (SINR) thresholds for different MCSs specified in 802.11g[6]. In our propagation model, the SINR of received signal is $\frac{\rho}{Dist^{\alpha}N_0}$, where $Dist$ is the distance between the AP and the station. The attenuation coefficient, i.e., α, is set to 3.5, and the noise floor, i.e., N_0, is set to -174 dBm. The maximum transmission power is set to 0.5mW/Hz. For simplicity, we omit the protocol overhead and assume that $o_{i,j}$ is fixed to 1. The QoS requirement is randomly generated from 1 to 5 (Mbps). Furthermore, $\varepsilon_1 = 0.1$, $\varepsilon_2 = 0.05$, $\eta_1 = 10$ and $\eta_2 = 100$.

Fig.1 (a) shows the convergence of LARD in the scenario of $M = 3$, $N = 6$, $\beta_k = 0.5$ and $\mu = 0.5$. The y-axis represents the probability that an AP is selected by the stations. It can be

[4]This statement can be verified by Definition 1 directly. The perturbation can be considered as the invader, and the unchanged steady state indicates that its utility is always higher than that of the invader.

[5]More detailed information is provided in the technical report at http://itec.hust.edu.cn/~yuanwei/Tech_report_AP_Selection_in_VWLANs.pdf

[6]According to 802.11 g, there are 8 MCSs which require different SINR thresholds to guarantee the correct decoding.



(a) Illustration of convergence of 6 stations (ST 1-6) selecting 3 APs (AP 1-3).

(b) Comparison of LARD and replicator dynamics with global information.

(c) Illustration of the impact of perturbation size on the system stability.

Fig. 1. Simulation results.

TABLE I
QoS SATISFACTION

Unit : Mbps		ST 1	ST 2	ST 3	ST 4	ST 5	ST 6
Case 1	MBR	3.98	2.07	3.21	2.48	1.90	4.79
	AB	6.0	6.0	4.0	3.0	3.0	6.0
Case 2	MBR	10.0	2.07	3.21	2.48	1.90	4.79
	AB	0	6.0	4.0	3.0	6.0	6.0

seen that stations converge to a pure-strategy profile within less than 30 iterations. The impact of perturbation injection can be seen at the 16th iteration, where ST 5 switches from AP 1 to AP 2. It means that perturbation injection makes our algorithm rule out unstable steady states. We compare our algorithm with the traditional scheme requiring global information in Fig.1 (b). For illustration, the iterations of 4 stations are provided in this figure, denoted by ST 1-AP 3, ST 2-AP 1, ST 5-AP 3 and ST 6-AP 2, respectively. Both schemes obtain the same AP selection outcome and our scheme converges within reasonable iterations.

Now we use simulation to analyze the impact of perturbation size (i.e., ε_2). ε_2 is set to 0.05, 0.1 and 0.15, respectively. As shown in Fig. 1 (c), LARD converges to the ESS obtained by the global algorithm when ε_2 is 0.05 or 0.1. When ε_2 is increased to 0.15, divergence is observed. This is because a large perturbation makes the system easily get out of the attraction of current ESS, and oscillate among the attracting basins of multiple ESSs. Therefore, the perturbation size should be small enough and appropriately chosen.

We now investigate the QoS performance of LARD. In Table I, the QoS requirement is denoted by MBR, and the achieved bandwidth is represented by AB. We illustrate the simulation results of LARD under two different QoS requirement configurations. In the first configuration, the QoS requirements of 6 stations are randomly generated between 1 and 5 (Mbps). All the QoS requirements are found to be satisfied since they are in a reasonable range. In the second case, the QoS requirement of ST 1 is changed to a much larger value, i.e, 10 Mbps, and its achieved bandwidth becomes zero. This is because the QoS requirement of ST 1 cannot be satisfied in the first run of LARD, and then ST 1 disassociates with its AP. After the second run of LARD, the other stations can achieve an ESS that satisfies their QoS requirements. It can be seen from Table I that the achieved bandwidth of ST 5 is doubled in the latter case since more access time is obtained by ST 5. Hence, the admission control mechanism can guarantee the access of stations with a reasonable bandwidth requirement.

VI. CONCLUSION

This letter investigates the AP selection problem in V-WLANs using an evolutionary game theoretical approach. A distributed learning algorithm is developed to achieve an ESS in the game with local information only. Numerical results validate the convergence and the effectiveness of our algorithm.

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