Dynamically Tuning Aggression Levels for Capacity-Region-Aware Medium Access Control in Wireless Networks

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***Abstract*—We propose adaptive capacity-region-aware algorithms for medium access control in wireless networks. In particular, the proposed algorithms are aware of the information-theoretic capacity region of a multiple access channel. According to the proposed algorithms, a node dynamically adjusts its channel access strategy based on the previous strategies of other nodes and the channel feedback. A strategy is composed of a transmission threshold and an aggression level. We propose symmetric learning algorithms for maximizing throughput. In addition, we propose asymmetric learning algorithms to strike a good balance between throughput and fairness. Furthermore, we propose novel methods to properly choose a finite number of available data transmission rates. We use both analytical results and simulation results to justify the usage of the proposed algorithms.**

***Index Terms*—Medium access control, capacity region, information theory, wireless networks.**

I. Introduction

WIRELESS local area networks (LANs) are widely deployed due to the large capacity and the low cost of deployment. Nodes in a wireless LAN share a common media. Based on the conventional $(0, 1, e)$ collision model, only one node can successfully transmit data in a time slot. If two or more nodes concurrently transmit data, the access point cannot successfully receive/decode any information from the nodes. It turns out that the collision model is too conservative. According to network information theory [1], multiple nodes could simultaneously and successfully transmit distinct data to the access point as long as the corresponding rate vector is inside the capacity region of the multiple access channel.

In the last decade, many works on wireless medium access control (MAC) with multipacket reception (MPR) capability emerged. Many of the works on MPR assumed that the data transmission rate is constant and the multiple access channel is completely characterized by the MPR matrix [2]. In particular, the total number of packets that can be successfully received/decoded by the access point in a time slot statistically depends only on the total number of nodes that transmit packets in the time slot. In this paper, we study the more general case in which the data transmission rate changes with the instantaneous channel gain and the total number of bits that can be successfully received/decoded by the access point in a time slot depends on the data transmission rates of all nodes in the network.

In this paper, we proposed capacity-region-aware, adaptive medium access control algorithms to improve the throughput and the fairness. The proposed algorithms explicitly exploit the information-theoretic capacity region of a multiple access channel. According to the proposed algorithms, in the end of a time slot, the access point broadcasts not only the list of the nodes that successfully transmit in the current time slot but also their current channel access strategies. Upon receiving the broadcast information, a node could dynamically adjust its own strategy of channel access in order to improve the network throughput. In particular, the strategy of a node in a time slot consists of a transmission threshold and an aggression level. The transmission threshold is used to determine whether or not a node can transmit data based on the instantaneous channel gain. The aggression level is used to control the transmission rate of a node so that the access point has a better chance to simultaneously receive/decode data from two or more nodes. We design and evaluate a variety of approaches for a node to dynamically tune its transmission strategy. Our simulation results show that the proposed algorithms could significantly outperform the slotted ALOHA protocol and the GDP protocol [3]. We also show that the network throughput of the proposed distributed algorithms could be as large as 80% of the network throughput of the ideal centralized algorithm.

Our major technical contributions include the following. First, to the best of our knowledge, our work is the first distributed algorithm of medium access control that explicitly exploits the information-theoretic capacity region of a multiple access channel in the literature. In addition, we propose using both the transmission threshold and the aggression level to decide the data transmission rate of a node. Furthermore, we propose efficient learning algorithms for a node to update its strategy of channel access based on the previous strategies of other nodes and the channel feedback. We also propose novel methods to properly choose a finite number of available data transmission rates.

The rest of the paper is organized as follows. Section II covers the related work. In Section III, we present the formal system models. In Section IV, we propose the symmetric

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learning algorithm that is design to maximize the network throughput of wireless medium access control. In Section V, we present the asymmetric learning algorithm, which is designed to strike a good balance between throughput and fairness in a heterogeneous wireless local area network. In Section VI, we propose novel methods to properly choose a finite number of available data transmission rates. In Section VII, we show simulation results that justify the usage of the proposed approach. Our conclusions are included in Section VIII. Related mathematical proofs are included in the Appendix.

II. Related Work

Adaptive algorithms were proposed to reduce the packet collision probability and improve the network throughput in wireless LANs. He, Sun, Ma, Vasilakos, Yuan, and Gong [4] proposed a semi-random backoff scheme in which a node adopts deterministic backoff after a successful packet transmission. Hauksson and Alanyali [5] proposed a random access mechanism with adaptive backoff for minimizing the packet delay and the packet loss probability. Lee, Chiang, and Calderbank [6] used a persistence-probabilistic model where a node adjusts its persistence probability according to its local information and message passing. Mohsenian-Rad, Huang, Chiang, and Wong [7] proposed distributed fast-converging algorithms where a node updates its transmission probability with message passing. In addition, they [8] proposed an ALOHA-type random access protocol where a node updates its transmission probability without message passing. Lin and Feng [9] proposed an adaptive reservation-assisted collision resolution (ARCR) protocol that combines the conventional DCF scheme in the IEEE 802.11 standard with piggyback.

Cross-layer design for medium access control based on the properties of wireless channels had been proposed to improve the network performance. Wang and Kar [10] proposed two cross-layer algorithms where the rates of end-to-end sessions are adjusted at the transport layer and the link attempt probabilities are adjusted at the link layer. Zheng, Pun, Ge, Zhang, and Poor [11] proposed a distributed opportunistic scheduling algorithm that includes channel estimation. Eshet and Liang [12] proposed a MAC protocol named randomly ranked mini slots (RRMS) where each node generates its rank per mini slot and the node with the highest rank can transmit data. Su and van der Schaar [13] proposed a distributed random access mechanism based on bio-inspired learning.

Utilizing multipacket reception (MPR) capability had been seen as a promising direction to increase the network throughput without increasing the required bandwidth. With MPR capability, multiple nodes are allowed to transmit concurrently. There are three well-known classes of distributed algorithms for medium access control: ALOHA, CSMA, and tree/stack splitting. Seo and Leung [14] proposed contention resolution algorithms for the multi-packet reception system where retransmission probability depends on the system backlog. Minero and Franceschetti [15] proposed a random access scheme for slotted ALOHA system with MPR capability in which nodes dynamically adjust their transmission rates and transmission probabilities. Guo, Wang, and Wu [16] analyzed the system capacity under the assumption that each node can successfully receive packets from at most k nodes. Gau [17] [18] analyzed the saturation/unsaturation throughput for the slotted ALOHA wireless networks with MPR capability. Dua [19] analyzed the performance of a user-centric slotted ALOHA network with MPR capability based on the queue size of a node. Yim, Mehta, Molisch, and Zhang [20] proposed utilizing the current local channel information to limit received signal power for the realization of MPR. Celik, Zussman, Khan, and Modiano [3] proposed an alternative backoff mechanism in which the transmission probability depends on the system state. Huang, Letaief, and Zhang [21] proposed a random access scheme in which nodes dynamically adjust the transmission probability according to the network population and the channel state information. Gau [22] used Poisson random traffic model to analyze the performance of the slotted nonpersistent CSMA protocol with MPR capability. Gau and Chen [23] derived novel analytical results for the performance of the classic tree/stack splitting algorithm in finite wireless networks with MPR. In addition, Gau [24] proposed the tree/stack splitting with remainder algorithm for distributed media access control in a wireless network with an arbitrary MPR channel matrix. Instead of SINR at the receiver or the MPR channel matrix, in this paper, we adopt network information theory [1] to determine whether or not data transmission in a time slot is successful.

Game theory has been widely used for medium access control. However, game theory is beyond the scope of this paper. Cui, Chen, and Low [25] modeled the behaviors of nodes as a game where each node observes some contention measure signals to determine the transmission probability. Jin and Kesidis [26] treated the competition between nodes as a non-cooperative game where nodes can choose their backoff contention window sizes. Inaltekin and Wicker [27] proposed a random access game where the transmission probability of each node will be determined based on game theory. Chen, Low, and Doyle [28] proposed a game-theoretic random access scheme where each node adjusts the persistence probability based on the conditional collision probability. Cho, Hwang, and Tobagi [29] proposed using game theory to design robust random access protocols for wireless networks. Nuggehalli, Sarkar, Kulkarni, and Rao [30] performed a game-theoretic analysis of quality-of-service in wireless medium access control. A survey on game-theoretic approaches for multiple access in wireless networks can be found in [31].

Power control has been extensively studied for sum rate maximization in a wireless network. Recently, Tan, Chiang, Srikant [32] studied the problem of sum rate maximization by power control in a wireless network, which is a NP-hard problem. They focused on finding approximately optimal solutions that can be efficiently computed. While they treat interference as noise and do not use successive interference cancellation, we study the case in which successive interference cancellation is used for the access point to decode packets from distinct nodes in a time slot. An introduction to power control in wireless networks can be found in [32] and reference therein. It is expected that dynamically tuning both the aggression level and the transmission power could further improve the system performance at the cost of an increase in computational complexity. However, joint optimization of aggression level

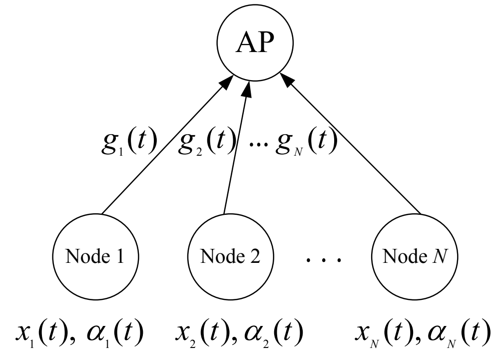

Fig. 1. Network model.

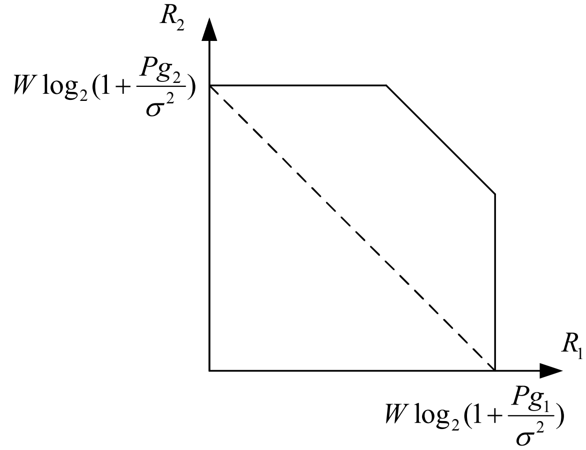

Fig. 2. Capacity region for N = 2.

and transmission power is beyond the scope of this paper.

III. System Models

In Figure 1, we show our network model. There are $N \geq 2$ nodes and an access point (AP) in the network. The time domain is divided into time slots of fixed length. The length of a time slot is smaller than the coherence time of the wireless channel. Without loss of essential generality, it is assumed that the length of a time slot equals one. Time slot t is the time interval $[t, t+1]$, $\forall t \geq 0$. Let W be the bandwidth, P be the maximum transmission power of a node in a time slot, $P_i(t)$ be the transmission power of node i at time slot t, and σ^2 be the power spectral density of the additive white Gaussian noise. Let $g_i(t)$ be the channel gain from node i to the AP in time slot t. For each fixed i, $g_i(t)$'s are independent and identically distributed continuous random variables. Define $F_i(u) = P\{g_i(t) \leq u\}$, $\forall i, t, u$. Let $\frac{1}{\lambda_i}$ be the expected value of $g_i(t)$, $\forall i, t$. When it is clear from the context, $g_i(t)$ is abbreviated by g_i. Let $A(t)$ be the set that is composed of the indexes of the nodes that transmit data in time slot t. Let $R_i(t)$ be the data transmission rate of node i in time slot t. Note that if $i \notin A(t)$, $R_i(t) = 0$. According to network information theory [1], $(R_1(t), R_2(t), .., R_N(t))$ is in the capacity region if and only if

$$\begin{aligned} R_i(t) &< W \cdot \log_2\left(1 + \frac{P_i(t) \cdot g_i(t)}{\sigma^2}\right), \forall i \\ \sum_{i \in S} R_i(t) &< W \cdot \log_2\left(1 + \frac{1}{\sigma^2} \sum_{i \in S} P_i(t) \cdot g_i(t)\right), \\ & \quad \forall S \subset A(t). \end{aligned} \tag{1}$$

If $(R_1(t), R_2(t), .., R_N(t))$ is in the above capacity region, all nodes that transmit data in time slot t successfully deliver their data to the access point. Otherwise, it is assumed that the access point fails to receive/decode any data in time slot t. Since it is desired to maximize the sum rate of all nodes in each time slot, in this paper, we focus on the case in which $P_i(t) = P$, $\forall i, t$. As shown in Figure 2, when $N = 2$, the capacity region is a pentagon. As long as $(R_1(t), R_2(t))$ is inside the pentagon, the concurrent data transmission is successful. In contrast, when a conventional time-division multiple-access scheme is used, for the access point to successfully receive/decode data in time slot t, $(R_1(t), R_2(t))$ has to be inside the triangle bounded by the dashed line, the x-axis, and the y-axis.

We study the saturation case in which a node always has data to transmit. The strategy of a node in a time slot is composed of a transmission threshold and an aggression level. Let $x_i(t)$ be the transmission threshold of node i in time slot t. Let $\alpha_i(t)$ be the aggression level of node i in time slot t. Note that $0 \leq \alpha_i(t) \leq 1$. Let $\epsilon > 0$ be a very small real number. If $g_i(t) < x_i(t)$, node i does not transmit any data in time slot t. On the other hand, if $g_i(t) \geq x_i(t)$, node i will transmit data with rate $\alpha_i(t) \cdot W \cdot \log_2(1 + \frac{P \cdot g_i(t)}{\sigma^2}) - \epsilon$ in time slot t. In this paper, to make the presentation concise, that a node transmits with rate R means the node transmits with rate $R - \epsilon$.

It is assumed that at the beginning of time slot t, the AP broadcasts a pilot signal for each node i to obtain the value of $g_i(t)$ through channel estimation. There are two approaches for node i to transmit the value of $(g_i(t), x_i(t), \alpha_i(t), R_i(t))$ to the access point in time slot t. In the first approach, there exists a mini slot at the beginning of a time slot. A mini slot is composed of $S \geq N$ orthogonal channels. Different nodes use distinct orthogonal channels to transmit the value of $(g_i(t), x_i(t), \alpha_i(t), R_i(t))$ to the access point at the beginning of time slot t. In the second approach, the value of $(g_i(t), x_i(t), \alpha_i(t), R_i(t))$ is included in the header of the data packet transmitted from node i to the access point in time slot t. When the first approach is used, there is no collision in a mini slot. When the second approach is used, in a time slot, if the rate vector is not within the capacity region, the AP does not know the current strategies and each node has to estimate the current strategies of other nodes.

Let $\zeta(t) \in \{0, 1, 2\}$ be the channel feedback in time slot t. In particular, if no nodes transmit data and therefore the channel is idle in time slot t, $\zeta(t) = 0$. In addition, if at least one node successfully transmits data in time slot t, $\zeta(t) = 1$. If some nodes transmit data but none of them succeed in time slot t, $\zeta(t) = 2$. At the end of time slot t, the AP broadcasts the value of $\zeta(t)$. In addition, if the rate vector is within the capacity region in time slot t, the AP broadcasts the values of $A(t)$ and $(x_i(t), \alpha_i(t), R_i(t))$'s, $1 \le i \le N$.

In this paper, we study the problem of distributed medium access control based on the information-theoretic capacity region. In particular, to optimize the network throughput or the fairness index, a node independently and dynamically adjusts its data transmission rate based on the information broadcast by the access point in the previous time slots and its own channel gain in the current time slot. Since we focus on distributed medium access control, a node has to adjust the data transmission rate without knowing the current channel gains of other nodes. We propose adjusting the data transmission rate through strategy learning.

IV. Symmetric Learning Algorithms

In this section, we propose the symmetric learning algorithm for capacity-region-aware wireless medium access control. Based on the algorithm, each node dynamically adjusts its strategy based on the previous strategies of other nodes and the channel feedback. There are two variants for the symmetric learning algorithm. The first variant is called Learn-from-the-best, while the second variant is called Learn-from-betters. For illustration purposes, we divide the algorithm into three parts: the main function and two additional functions. We first introduce the main function. Consider node i in time slot t. At the beginning of the time slot, the access point broadcasts pilot signals for each node to estimate the corresponding channel gain. If $g_i(t) \ge x_i(t)$, $R_i(t) = \alpha_i(t) \times \log_2(1 + \frac{P \cdot g_i(t)}{\sigma^2})$ and node i transmits data to the access point with rate equals $R_i(t)$ till the end of time slot t. Otherwise, node i does not transmit any data in time slot t and $R_i(t) = 0$. In the end of time slot t, the access point broadcasts the values of $\zeta(t)$, $A(t)$, and $(x_i(t), \alpha_i(t), R_i(t))$'s, $1 \le i \le N$. Pseudo codes for the above procedure are included in Algorithm 1.

We now explain how a node updates its strategy when $\zeta(t) = 0$. Let $f_2 \in (0, 1)$ be a real number. Note that $\zeta(t) = 0$ implies that none of the nodes transmit data in time slot t. Therefore, when $\zeta(t) = 0$, to increase the probability that at least one node transmits data in time slot $t+1$, the transmission threshold at time slot $t+1$ is set to a small real number. In particular, $x_i(t+1)$ is set to $f_2 \cdot \min_{j:1\le j\le N} x_j(t)$.

We now elaborate on how a node updates its strategy when $\zeta(t) = 1$. Note that $\zeta(t) = 1$ implies that one or more nodes successfully transmit data in time slot t. In a time slot, the strategy of node i is said to be better than the strategy of node j, if the data rate of node i is greater than the data rate of node j. The best strategy in a time slot is defined to be the strategy used by the node with the maximum data rate in the time slot. Let i^* be the index of the node with the best strategy in time slot t. Let $f_1 > 1$ be a real number. When the Learn-from-the-best algorithm is used, node i adopts the best strategy in time slot t as its strategy in time slot $t+1$. In addition, to further increase the network throughput, node i^* increases its aggression level. In particular, $\alpha_{i^*}(t+1) = \alpha_{i^*}(t) \cdot f_1$. When the Learn-from-betters algorithm is used, node i first calculates the arithmetic average of the strategies which are better than the strategy of node i. Then, node i adopts the average as the strategy in time slot $t+1$. In addition, to further increase the network throughput, node i^* increases its aggression level. In particular, $\alpha_{i^*}(t+1) = \alpha_{i^*}(t) \cdot f_1$. Pseudo codes for the above procedure are included in Algorithm 2.

Algorithm 1 : The proposed algorithm (for node i in time slot t)

Input: P, σ^2, and W.
Output: $R_i(t)$.

if $t == 0$ **then**
  $f_1 = 1.01$, $f_2 = 0.9$.
  $x_i(0) = 0$, $\alpha_i(0) = 0.1$.
end if
$R_i(t) = 0$.
Obtain the value of $g_i(t)$ through channel estimation.
if $g_i(t) \ge x_i(t)$ **then**
  $R_i(t) = \alpha_i(t) \times \log_2(1 + \frac{P \cdot g_i(t)}{\sigma^2})$.
  Transmit data at rate equals $R_i(t)$ till the end of the time slot.
else
  Wait until the end of the time slot.
end if
At time $(t+1)$, obtain the values of $\zeta(t)$, $A(t)$, and $(x_i(t), \alpha_i(t), R_i(t))$'s broadcast from the access point.
if $\zeta(t) == 0$ **then**
  // none of the nodes transmitted data
  $x_i(t+1) = f_2 \cdot \min_{j:1\le j\le N} x_j(t)$.
  $\alpha_i(t+1) = \alpha_i(t)$
end if
if $\zeta(t) == 1$ **then**
  // one or more nodes successfully transmitted data
  Calculate $(x_i(t+1), \alpha_i(t+1))$ by Algorithm 2.
end if
if $\zeta(t) == 2$ **then**
  // a collision occurs
  Calculate $(x_i(t+1), \alpha_i(t+1))$ by Algorithm 3.
end if

We now elaborate on how a node updates its strategy when $\zeta(t) = 2$. Note that $\zeta(t) = 2$ means that one or more nodes transmit data in time slot t but none of them succeed. Thus, it is desired for nodes to decrease their aggression levels. Let $f_2 \in (0, 1)$ be a real number. When the Learn-from-the-best algorithm is used, the minimum value among the aggression levels that are used by active nodes in time slot t is seen as the best aggression level for time slot t. Therefore, $\alpha_i(t+1)$ is set to $\min_{j:j\in A(t)} \alpha_j(t) \cdot f_2$. For node $i \notin A(t)$, in order to increase its transmission probability, $x_i(t+1)$ is set to $\min_{j:j\in A(t)} x_j(t)$. When the Learn-from-betters algorithm is used, a node first calculates $\overline{\alpha}(t)$, which is the arithmetic average of the aggression levels used by active nodes in time slot t. Then, $\alpha_i(t+1)$ is set to $\overline{\alpha}(t) \cdot f_2$. For $i \notin A(t)$, in order to increase its transmission probability, node i calculates $\overline{x}(t)$, the arithmetic average of the transmission thresholds used by active nodes in time slot t. Then, $x_i(t+1)$ is set to $\overline{x}(t)$. Pseudo codes for the above procedure are included in Algorithm 3.

Node j is said to be the winner of time slot t, if $\zeta(t) = 1$ and $R_j(t) > R_i(t)$, $\forall i \ne j$. Recall that channel gains

Algorithm 2 : Calculating $x_i(t+1)$ and $\alpha_i(t+1)$, when $\zeta(t) = 1$ (for node i)

Output: $x_i(t+1)$ and $\alpha_i(t+1)$.
$i^* = \arg\max_{i:i \in S(t)} R_i(t)$
if $LearnFromTheBest == True$ **then**
  $x_i(t+1) = x_{i^*}(t)$.
  if $i == i^*$ **then**
    $\alpha_{i^*}(t+1) = \alpha_{i^*}(t) \cdot f_1$.
  else
    $\alpha_i(t+1) = \alpha_{i^*}(t)$.
  end if
end if
if $LearnFromBetters == True$ **then**
  // find out all the nodes that perform better than node i in time slot t
  $\Phi_i(t) = \{j | R_j(t) > R_i(t)\}$.
  if $|\Phi_i(t)| \geq 1$ **then**
    $x_i(t+1) = \frac{1}{|\Phi_i(t)|} \sum_{j:j \in \Phi_i(t)} x_j(t)$.
    $\alpha_i(t+1) = \frac{1}{|\Phi_i(t)|} \sum_{j:j \in \Phi_i(t)} \alpha_j(t)$.
  else
    // increase the aggression level of the best node in time slot t
    $x_i(t+1) = x_i(t)$.
    $\alpha_i(t+1) = \alpha_i(t) \cdot f_1$.
  end if
end if

are realizations of continuous random variables. Therefore, the probability that two channel gains are identical is zero. Similarly, the probability that the data transmission rates of two nodes in a time slot are equivalent is zero. Let $w(t)$ be the index of the winner in time slot t. In order to study how aggression levels change with time, define $\alpha'(t) = \frac{1}{N} \sum_{i=1}^{N} |\alpha_i(t) - \alpha_i(t-1)|$. We now show two theorems for the proposed symmetric learning algorithms.

Theorem 1: For the Learn-from-the-best algorithm, if $\zeta(t) = \zeta(t+1) = 1$ and $w(t) = w(t+1)$, $\alpha_i(t+2) > \alpha_i(t+1), \forall i$.

Proof: See Appendix.

Consider the Learn-from-the-best algorithm. The above theorem corresponds to a sufficient condition for all nodes to simultaneously increase their aggression levels. In particular, if there exist two consecutive time slots in which the AP successfully receives data and the winners are the same, each node increases its aggression level right after the two time slots.

Theorem 2: When either the Learn-from-the-best algorithm or the Learn-from-betters algorithm is used, if $x_i(0) = 0$, $\forall i$, $\alpha'(t) > 0$, $\forall t$.

Proof: See Appendix.

Consider either the Learn-from-the-best algorithm or the Learn-from-betters algorithm. According to the above theorem, if the initial threshold of each node is zero, in each time slot, at least one node changes its aggression level. Therefore, if the set of current strategies corresponds to a local optimal point, it is assured that the set of the updated strategies will be different. Namely, the algorithm will not be trapped in a local optimal point forever.

Algorithm 3 : Calculating $x_i(t+1)$ and $\alpha_i(t+1)$, when $\zeta(t) = 2$ (for node i)

Output: $x_i(t+1)$ and $\alpha_i(t+1)$.
if $LearnFromTheBest == True$ **then**
  $\alpha_i(t+1) = f_2 \cdot \min_{j:j \in A(t)} \alpha_j(t)$.
  if $i \in A(t)$ **then**
    $x_i(t+1) = x_i(t)$.
  else
    $x_i(t+1) = \min_{j:j \in A(t)} x_j(t)$.
  end if
end if
if $LearnFromBetters == True$ **then**
  $\overline{\alpha}(t) = \frac{1}{|A(t)|} \sum_{j:j \in A(t)} \alpha_j(t)$.
  $\alpha_i(t+1) = \overline{\alpha}(t) \cdot f_2$.
  if $i \in A(t)$ **then**
    $x_i(t+1) = x_i(t)$.
  else
    $\overline{x}(t) = \frac{1}{|A(t)|} \sum_{j:j \in A(t)} x_j(t)$.
    $x_i(t+1) = \overline{x}(t)$.
  end if
end if

V. Asymmetric Learning Algorithms

In this section, we propose the asymmetric learning algorithm that is designed to strike a good balance between throughput and fairness. In contrast, the symmetric learning algorithm is designed to maximize the throughput. The asymmetric learning algorithm is based on the symmetric learning algorithm. As the symmetric learning algorithm, the asymmetric learning algorithm has two variants: Learn-from-the-best and Learn-from-betters. Between the two variants, we focus on the Learn-from-the-best algorithm. The major difference between the asymmetric learning algorithm and the symmetric learning algorithm lies in the procedure of setting the initial aggression levels. Let μ_i be the expected value of the maximum achievable transmission rate of node i in a time slot. Recall that $F_i(u)$ is the cumulative density function of the continuous random variable g_i. Then, according to information theory and probability theory,

$$\begin{aligned} \mu_i &= \mathbf{E}[W \log_2(1 + \frac{P \cdot g_i}{\sigma^2})] \\ &= \int_0^\infty W \log_2(1 + \frac{P \cdot u}{\sigma^2}) \, dF_i(u). \end{aligned} \tag{2}$$

Note that the integral in the right-hand side of the second equality is the Riemann-Stieltjes integral.

Let $\alpha \in (0, 1)$ be a real number. According to the asymmetric learning algorithm,

$$\alpha_i(0) = \alpha \cdot \frac{\min_{1 \leq j \leq N} \mu_j}{\mu_i}. \tag{3}$$

Note that $\frac{\min_{1 \leq j \leq N} \mu_j}{\mu_i} \in [0, 1]$ and therefore $\alpha_i(0) \in [0, 1]$. In addition, to improve fairness, nodes with worse channels have larger initial aggression levels.

We now elaborate on the procedure for a node to update its transmission strategy. When $\zeta(t) = 0$, the update procedure of the asymmetric learning algorithm is the same as that of the symmetric learning algorithm. Recall that when $\zeta(t) = 1$, the node with the largest data transmission rate in time slot t is said to be the winner in time slot t. When $\zeta(t) = 1$, in order to increase the throughput, node i increases its aggression level if (and only if) the total number of times being the winner up to time slot t is an even number. In this case, $\alpha_i(t+1) = \alpha_i(t) \cdot f_1$, where $f_1 > 1, \forall i$. When $\zeta(t) = 2$, to avoid persistent collisions, nodes decrease their aggression levels. In particular, $\alpha_i(t+1) = \alpha_i(t) \cdot f_2$, where $0 < f_2 < 1, \forall i$.

VI. A Finite Number of Available Transmission Rates

In this section, we study the case in which the set of available transmission rates is finite and predetermined. We propose novel methods to determine the values of the available transmission rates. Let $K \geq 1$ be an integer. Let $R_1, R_2, .., R_K$ be positive real numbers. In addition, $R_i < R_{i+1}$, $\forall 1 \leq i \leq K-1$. $R_1, R_2, .., R_K$ are called the available transmission rates. Consider a node in a time slot. Let X be the maximum achievable transmission rate for the node in the time slot. If $X < R_1$, the node does not transmit data in the time slot. If there exists an integer $j \in \{1, 2, .., K-1\}$ such that $X \in [R_j, R_{j+1})$, the node transmits with rate R_j in the time slot. If $X \geq R_K$, the node transmits with rate R_K in the time slot. Let Y be a random variable that represents the transmission rate of the node in the time slot.

We focus on homogeneous Rayleigh fading networks in which $F_i(u) = 1 - e^{-\lambda u}$, $\forall 1 \leq i \leq N, u \geq 0$. Since the analysis for all time slots are the same, it is sufficient to consider a time slot. Let $(R_1^*(N), R_2^*(N), .., R_K^*(N))$ be the optimal value of $(R_1, R_2, .., R_K)$, when there are N nodes in the network. When $N = 1$, we abbreviate $R_i^*(1)$ by R_i^*, $\forall 1 \leq i \leq K$.

A. When $K = 1$ and $N = 1$

We first consider the case in which $K = 1$ and $N = 1$. Let G be a random variable that represents the channel gain of the node in the time slot. Then, the random variable G is exponentially distributed with mean $\frac{1}{\lambda}$. According to information theory, $X = W \log_2(1 + \frac{P \cdot G}{\sigma^2})$. If $X \geq R_1$, $Y = R_1$. Otherwise, $Y = 0$. Let $f_X(\cdot)$ be the probability density function of the random variable X. Since $X = W \log_2(1 + \frac{P \cdot G}{\sigma^2})$, we have

$$f_X(x) = \frac{\lambda\sigma^2 \ln 2}{PW} e^{-\frac{\lambda\sigma^2}{P}(2^{\frac{x}{W}}-1)} 2^{\frac{x}{W}}. \quad (4)$$

Moreover,

$$\begin{aligned} \mathrm{E}[Y] &= \int_0^{R_1} 0 \cdot f_X(x)\,dx + \int_{R_1}^{\infty} R_1 \cdot f_X(x)\,dx \\ &= R_1 \cdot \int_{R_1}^{\infty} f_X(x)\,dx. \end{aligned} \quad (5)$$

In order to find the maximum value of $\mathrm{E}[Y]$, we define $g(R_1) = R_1 \cdot \int_{R_1}^{\infty} f_X(x)\,dx$. Then,

$$\begin{aligned} & \frac{dg(R_1)}{dR_1} \\ =\; & \int_{R_1}^{\infty} f_X(x)dx - R_1 f_X(R_1) \\ =\; & e^{-\frac{\lambda\sigma^2}{P}(2^{\frac{R_1}{W}}-1)}\left(1 - \frac{\lambda\sigma^2 \ln 2}{PW} R_1 2^{\frac{R_1}{W}}\right) \\ =\; & e^{-\frac{\lambda\sigma^2}{P}(2^{\frac{R_1}{W}}-1)}\left(\frac{-\lambda\sigma^2 \ln 2}{PW}\right)\left(R_1 \cdot 2^{\frac{R_1}{W}} - \frac{PW}{\lambda\sigma^2 \ln 2}\right). \end{aligned} \quad (6)$$

In order to find the roots of $g'(R_1)$, we define $h(R_1)$ as follows.

$$h(R_1) = R_1 \cdot 2^{\frac{R_1}{W}} - \frac{PW}{\lambda\sigma^2 \ln 2}. \quad (7)$$

Then, $h''(R_1) = \frac{\ln 2}{W} 2^{\frac{R_1}{W}}(2 + \frac{\ln 2}{W} R_1)$. Since $h''(R_1) > 0$, $\forall R_1 \geq 0$, $h(R_1)$ is a convex function in $[0, \infty)$. In addition, $h(0) = -\frac{PW}{\lambda\sigma^2 \ln 2} < 0$. Thus, $h(R_1)$ has a unique root in $(0, \infty)$.

Since $e^{-x} > 0$, $\forall x$, and that $h(R_1)$ has a unique root in $(0, \infty)$, based on Equation (6), $g'(R_1)$ has a unique root in $(0, \infty)$. Namely, $g(R_1)$ has a unique interior local optimal point in $(0, \infty)$, denoted by L^*.

We now show that L^* is also the unique global optimal point for $g(R_1)$ in $[0, \infty)$. Clearly, $g(L^*) > 0$ and $g(0) = 0$. In addition,

$$\begin{aligned} \lim_{R_1 \to \infty} g(R_1) &= \lim_{R_1 \to \infty} R_1 e^{-\lambda R_1} \\ &= 0. \end{aligned} \quad (8)$$

Therefore, for $g(R_1)$, L^* is also the unique global optimal point in $[0, \infty)$. We set $R_1^* = L^*$. The value of L^* can be found by numerical methods such as the Newton-Raphson method [33].

B. When $K = 1$ and $N \geq 2$

We now propose a novel method to determine the optimal values for the available transmission rates, when $K = 1$ and $N \geq 2$. Based on the principle of symmetry, it is assumed that as time goes to infinity, the aggression levels of N nodes converge to the same number α_N. We use the following method to derive the approximated value of α_N. First, based on Equation (1), we have

$$\alpha_N \log_2 \prod_{i=1}^{N}(1 + \frac{P g_i}{\sigma^2}) < \log_2(1 + \frac{P}{\sigma^2}\sum_{i=1}^{N} g_i). \quad (9)$$

Replacing g_i in the above equation by $\frac{1}{\lambda}$, we have

$$\alpha_N \log_2(1 + \frac{P}{\sigma^2 \lambda})^N < \log_2(1 + \frac{PN}{\sigma^2 \lambda}). \quad (10)$$

Since nodes learn to maximize their transmission rates, we substitute the inequality in the above equation by equality and get the following equation.

$$\alpha_N = \log_{(1+\frac{P}{\sigma^2 \lambda})^N}(1 + \frac{PN}{\sigma^2 \lambda}). \quad (11)$$

In addition, $X = \alpha_N \cdot W \cdot \log_2(1 + \frac{P \cdot G}{\sigma^2})$. Then,

$$f_X(x) = \frac{\lambda\sigma^2 \ln 2}{P\alpha_N W} e^{-\frac{\lambda\sigma^2}{P}(2^{\frac{x}{\alpha_N W}}-1)} 2^{\frac{x}{\alpha_N W}}. \tag{12}$$

Moreover,

$$\mathrm{E}[Y] = R_1 \cdot \int_{R_1}^{\infty} f_X(x)dx. \tag{13}$$

In order to find the maximum value of $\mathrm{E}[Y]$, we have

$$\begin{aligned} \frac{dg(R_1)}{dR_1} &= e^{-\frac{\lambda\sigma^2}{P}(2^{\frac{R_1}{\alpha_N W}}-1)} \times (\frac{-\lambda\sigma^2 \ln 2}{P\alpha_N W}) \times \\ &\quad (R_1^N \cdot 2^{\frac{R_1}{\alpha_N W}} - \frac{P\alpha_N W}{\lambda\sigma^2 \ln 2}). \end{aligned} \tag{14}$$

In order to find the roots of $g'(R_1)$, we define $v(R_1)$ as follows.

$$v(R_1) = R_1 \cdot 2^{\frac{R_1}{\alpha_N W}} - \frac{P\alpha_N W}{\lambda\sigma^2 \ln 2}. \tag{15}$$

Then, based on Equation (7) and the definition of R_1^*, we have

$$\begin{aligned} v(\alpha_N R_1^*) &= \alpha_N \times h(R_1^*) \\ &= \alpha_N \times 0 \\ &= 0. \end{aligned} \tag{16}$$

Hence, we set the value of $R_1^*(N)$ as follows.

$$R_1^*(N) = \alpha_N \cdot R_1^*. \tag{17}$$

C. When $K \geq 2$

In this section, we first consider the case in which $N = 1$ and $K = 2$. Let $g_2(R_1, R_2)$ be the expected value of the transmission rate of the node in a time slot. Then,

$$\begin{aligned} &g_2(R_1, R_2) \\ &= R_1 \int_{R_1}^{R_2} f_X(x)dx + R_2 \int_{R_2}^{\infty} f_X(x)dx. \end{aligned} \tag{18}$$

Thus,

$$\begin{aligned} \frac{\partial g_2(R_1, R_2)}{\partial R_1} &= e^{-\frac{\lambda\sigma^2}{P}(2^{\frac{R_1}{W}}-1)}(1 - \frac{\lambda\sigma^2 \ln 2}{PW} R_1 2^{\frac{R_1}{W}}) \\ &\quad - e^{-\frac{\lambda\sigma^2}{P}(2^{\frac{R_2}{W}}-1)}. \end{aligned} \tag{19}$$

In addition,

$$\frac{\partial g_2(R_1, R_2)}{\partial R_2} = e^{-\frac{\lambda\sigma^2}{P}(2^{\frac{R_2}{W}}-1)}[\frac{\lambda\sigma^2 \ln 2}{PW}(R_1 - R_2)2^{\frac{R_2}{W}} + 1]. \tag{20}$$

Based on Calculus, (R_1^*, R_2^*) is a root of the following two equations.

$$\begin{aligned} &e^{-\frac{\lambda\rho^2}{P}(2^{\frac{R_2}{W}}-1)} \\ &= e^{-\frac{\lambda\sigma^2}{P}(2^{\frac{R_1}{W}}-1)} \times (1 - \frac{\lambda\sigma^2 \ln 2}{PW} R_1 2^{\frac{R_1}{W}}). \end{aligned} \tag{21}$$

$$R_1 = R_2 - \frac{PW}{\lambda\sigma^2 \ln 2} 2^{-\frac{R_2}{W}}. \tag{22}$$

Based on (22) and (21), R_2^* must be a root of $f(R_2)$, which is defined as follows.

$$\begin{aligned} &f(R_2) \\ &= e^{-\frac{\lambda\rho^2}{P}(2^{\frac{R_2}{W}}-1)} - e^{-\frac{\lambda\sigma^2}{P}(2^{(\frac{R_2}{W} - \frac{P}{\lambda\sigma^2 \ln 2}2^{-\frac{R_2}{W}})}-1)} \times \\ &\quad [1 - (\frac{\lambda\sigma^2 \ln 2}{PW} R_2 - 2^{-\frac{R_2}{W}})2^{\frac{R_2}{W} - \frac{P}{\lambda\sigma^2 \ln 2}2^{-\frac{R_2}{W}}}]. \end{aligned} \tag{23}$$

Theorem 3: $f(R_2)$ has one root in $[0, W \log_2 \frac{P}{\lambda\sigma^2 \ln 2}]$, if $\frac{P}{\lambda\sigma^2 8 \ln 2} > 1$.

Proof: See Appendix.

Note that $\frac{P}{\lambda\sigma^2}$ corresponds to the average signal-to-noise ratio. We use the binary search method to find out a root of $f(R_2)$ in $[0, W \log_2 \frac{P}{\lambda\sigma^2 \ln 2}]$. Next, R_2^* is set to the root. Note that the function f is not convex or concave. Given the value of R_2^*, the value of R_1^* can be obtained based on Equation (22).

We now consider the case in which $N \geq 2$ and $K = 2$. In this case, the optimal value of (R_1, R_2) has to satisfy the following equation.

$$\begin{cases} e^{-\frac{\lambda\rho^2}{P}(2^{\frac{R_2}{\alpha_N W}}-1)} = e^{-\frac{\lambda\sigma^2}{P}(2^{\frac{R_1}{\alpha_N W}}-1)} \times \\ (1 - \frac{\lambda\sigma^2 \ln 2}{P\alpha_N W} R_1 2^{\frac{R_1}{\alpha_N W}}) \\ R_1 = R_2 - \frac{P\alpha_N W}{\lambda\sigma^2 \ln 2} 2^{-\frac{R_2}{\alpha_N W}}. \end{cases} \tag{24}$$

Similar to the case in which $N \geq 2$ and $K = 1$, we have $R_1^*(N) = \alpha_N \cdot R_1^*$ and $R_2^*(N) = \alpha_N \cdot R_2^*$.

For the general case where $K \geq 3$, we can find out the optimal values for the available transmission rates by solving the following set of equations.

$$\begin{cases} e^{-\frac{\lambda\sigma^2}{P}(2^{\frac{R_2}{W}}-1)} = e^{-\frac{\lambda\sigma^2}{P}(2^{\frac{R_1}{W}}-1)}(1 - \frac{\lambda\sigma^2 \ln 2}{PW} R_1 2^{\frac{R_1}{W}}) \\ e^{-\frac{\lambda\sigma^2}{P}(2^{\frac{R_{k+1}}{W}}-1)} = e^{-\frac{\lambda\sigma^2}{P}(2^{\frac{R_k}{W}}-1)} \times \\ (1 + \frac{\lambda\sigma^2 \ln 2}{PW}(R_{k-1} - R_k)2^{\frac{R_k}{W}}), \quad 2 \leq k \leq K-1 \\ R_{K-1} = R_K - \frac{PW}{\lambda\sigma^2 \ln 2} 2^{-\frac{R_K}{W}}. \end{cases} \tag{25}$$

VII. Simulation Results

In this section, we show simulation results. We wrote a C++ program to obtain simulation results. The transmission power of a node is $P = 1$, while the power spectral density of the additive white Gaussian noise is $\sigma^2 = 0.01$. The bandwidth is $W = 20$ MHz. We first study a symmetric Rayleigh fading network in which the channel gain of a node is an exponentially distributed random variable with mean 1. We compare the proposed algorithms with the ideal centralized algorithm, the slotted ALOHA protocol, and the GDP protocol [3]. When the Learn-from-the-best algorithm, the Learn-from-betters algorithm, the slotted ALOHA protocol, or the GDP protocol is used, in a time slot, as long as the rate vector is within the capacity region, the access point successfully receives/decodes all packets transmitted in the time slot. The ideal centralized algorithm calculates the maximum sum rate of a time slot based on the instantaneous channel gains in the time slot and Equation (1). It is used to obtain an upper bound for the throughput of a distributed medium access control algorithm. Recall that N is the total number of nodes

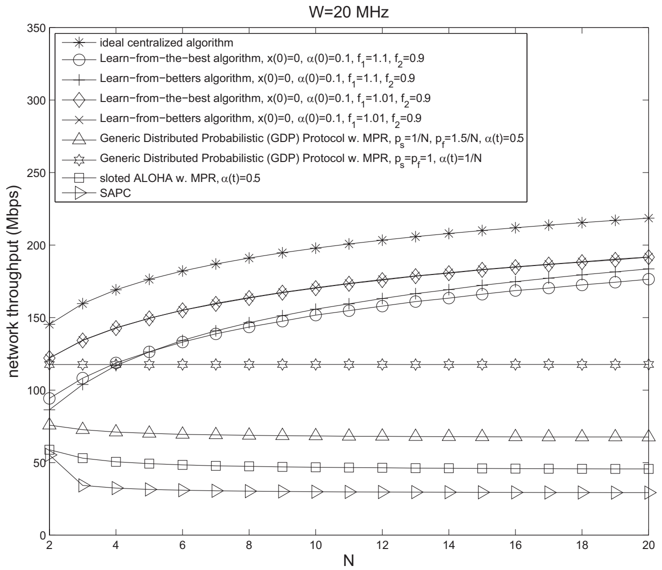

Fig. 3. Performance comparison of MAC algorithms.

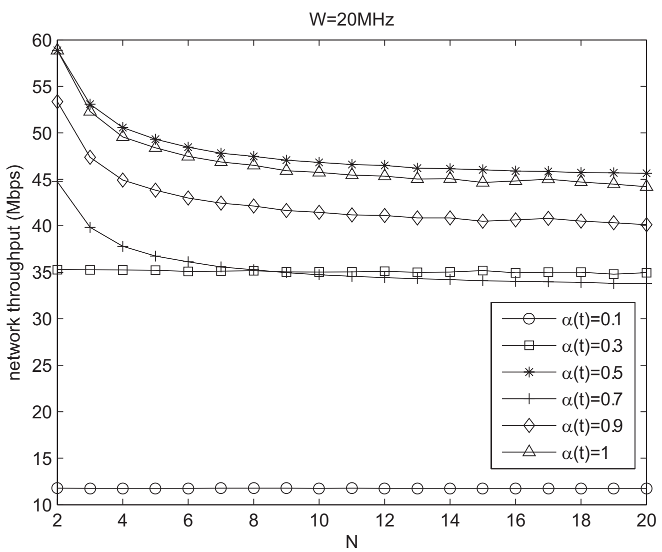

Fig. 4. Throughput of slotted ALOHA with different aggression levels.

in the network. When the slotted ALOHA protocol is used, the transmission probability of each node is $\frac{1}{N}$. When the GDP protocol is used, after a successful transmission, a node sets the next transmission probability to p_s. On the other hand, after an unsuccessful transmission, a node sets the next transmission probability to p_f. When either the slotted ALOHA protocol or the GDP protocol is used, all nodes always have the same aggression level. Namely, $\alpha_i(t) = \alpha(t)$, $\forall i, t$, and $\alpha(t)$ is a constant. Unless explicitly stated, $f_1 = 1.1$ and $f_2 = 0.9$ in this section.

Figure 3 shows the network throughput for the proposed symmetric learning algorithms, the slotted ALOHA protocol with $\alpha(t) = 0.5$, the GDP protocol with two sets of parameters, and the ideal centralized algorithm. In terms of the network throughput, the proposed learning algorithms significantly outperform the slotted ALOHA protocol and the GDP protocol with $(p_s, p_f, \alpha(t)) = (\frac{1}{N}, \frac{1.5}{N}, 0.5)$. In addition, the proposed Learn-from-the-best algorithm with $(f_1, f_2) = (1.01, 0.9)$ outperforms the GDP protocol with $(p_s, p_f, \alpha(t)) = (1, 1, \frac{1}{N})$. For example, the throughput of the Learn-from-the-best algorithm with $(f_1, f_2) = (1.1, 0.9)$ is about 2.6 times larger than that of the GDP protocol with $(p_s, p_f, \alpha(t)) = (\frac{1}{N}, \frac{1.5}{N}, 0.5)$ and about 3.8 times larger than that of the slotted ALOHA protocol. The performance improvement is due to that nodes could dynamically adjust their transmission rates based on the previous strategies used by other nodes. As long as the vector of transmission rates is within the capacity region, nodes continuously attempt to increase their transmission rates. When $(f_1, f_2) = (1.1, 0.9)$, the throughput of the Learn-from-the-best algorithm could be as large as 79.75% of the throughput of the ideal centralized algorithm. When $(f_1, f_2) = (1.1, 0.9)$, the throughput of the Learn-from-betters algorithm could be as large as 82.83% of the throughput of the ideal centralized algorithm. When $(f_1, f_2) = (1.01, 0.9)$, the throughput of the Learn-from-the-best algorithm is almost identical to that of the Learn-from-betters algorithm. The proposed algorithms outperform the slotted ALOHA protocol and the GDP protocol, since the proposed algorithms have more strategies to choose. The slotted ALOHA protocol has only one strategy, since the transmission probability is fixed. The GDP protocol has two strategies, since there are two possible transmission probabilities. Each of the proposed algorithms has infinitely many strategies, since the aggression level is a real number in the interval $[0, 1]$. Since the GDP protocol does not explicitly take the information-theoretic capacity region into consideration, it is possible to modify the GDP protocol to further improve the performance. However, such modifications are beyond the scope of the paper. We also study the performance of the SAPC algorithm [32], which is a fast power control algorithm that treats multiuser interference as noise and does not adopt successive interference cancellation (SIC). All the other studied algorithms adopt SIC, which increases the network throughput. Distributed optimal power control with SIC is beyond the scope of this paper.

Figure 4 shows the impacts of the aggression levels on the throughput of the slotted ALOHA protocol. We can see that the slotted ALOHA protocol reaches the maximum throughput when $\alpha(t) = 0.5$. If the value of $\alpha(t)$ decreases from 0.5, the throughput decreases since each node reduces its data transmission rate. If the value of $\alpha(t)$ increases from 0.5, the transmission rate vector becomes more likely to be outside the capacity region. Therefore, the throughput decreases. Figure 5 shows the impacts of the aggression levels on the throughput of the GDP protocol with $(p_s, p_f) = (\frac{1}{N}, \frac{1.5}{N})$. Based on the simulation results, the throughput of the GDP protocol with $(p_s, p_f) = (\frac{1}{N}, \frac{1.5}{N})$ is maximized when $\alpha(t) = 0.5$.

Figure 6 shows the impacts of $x(0)$ on the network throughput, when the proposed symmetric learning algorithm is used. The smaller the value of $x(0)$ is, the larger the network throughput is. In other words, allowing more nodes to transmit at time zero can increase the network throughput. Based on the proposed symmetric learning algorithm, nodes learn to adjust their transmission rates so that a number of nodes could successfully transmit at the same time. It should be noted that different nodes might transmit at different rates

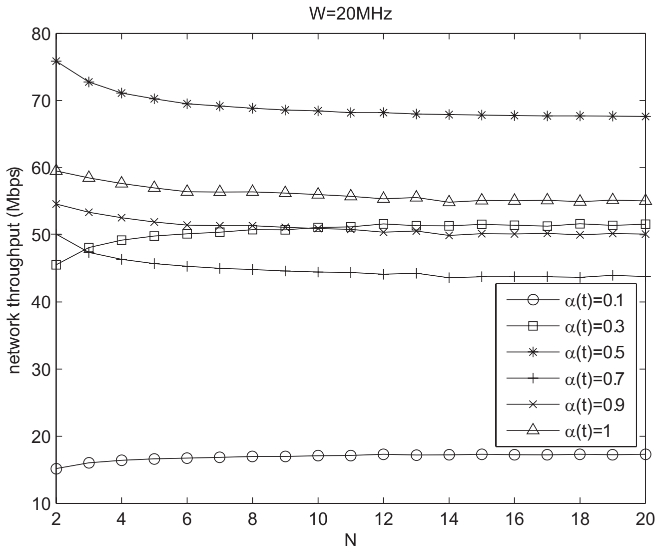

Fig. 5. Throughput of the GDP protocol with different aggression levels.

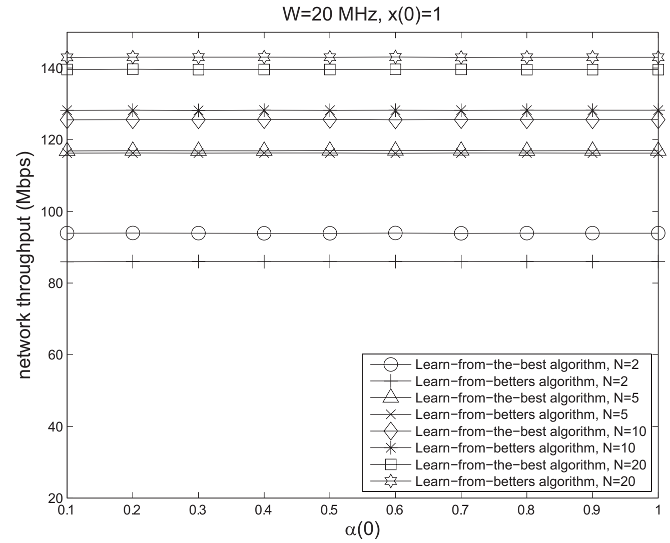

Fig. 7. Throughput under different values of $\alpha(0)$.

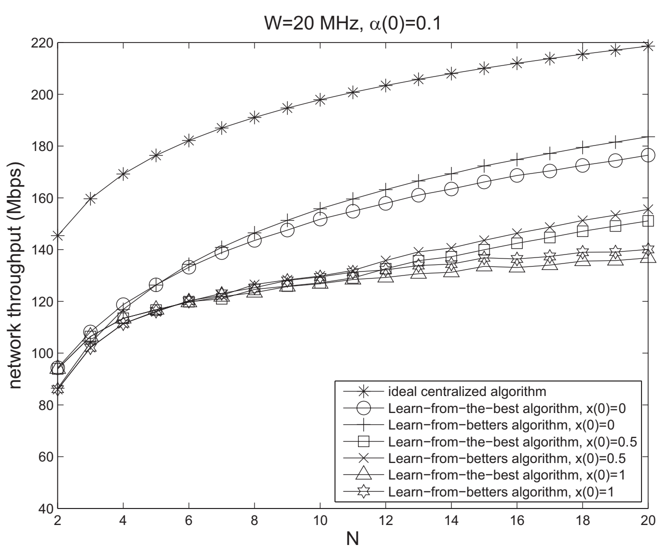

Fig. 6. Throughput under different values of $x(0)$.

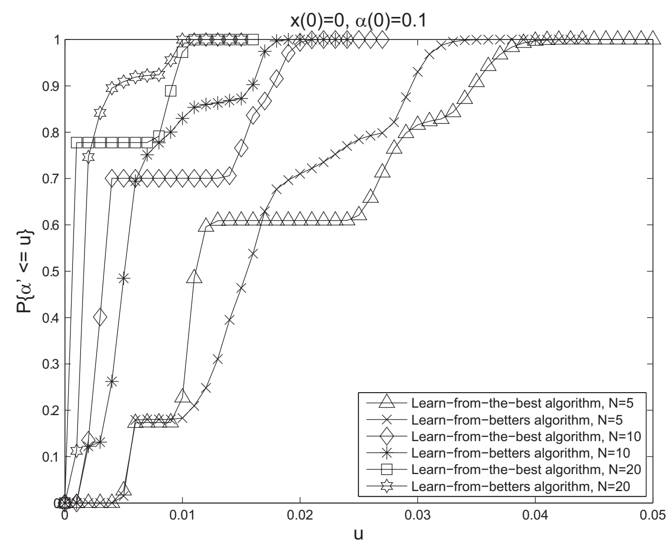

Fig. 8. The cumulative density function of α'.

in a time slot. Figure 7 shows the impacts of $\alpha(0)$ on the network throughput, when the proposed symmetric learning algorithm is used. Unlike $x(0)$, $\alpha(0)$ has no impacts on the network throughput. If the value of $\alpha(0)$ is too large, the initial transmissions would fail. In this case, nodes will learn to decrease their aggression levels to make future transmissions successful. On the other hand, if the value of $\alpha(0)$ is too small, in the first few time slots, many nodes will transmit successfully but the average throughput will be small. In this case, nodes will learn to increase their aggression levels in order to increase the network throughput.

Since $\alpha'(t) = \frac{1}{N}\sum_{i=1}^{N} |\alpha_i(t) - \alpha_i(t-1)|$, it can be seen as a random variable denoted by α'. Figure 8 shows the cumulative density function of α'. For both the Learn-from-the-best algorithm and the Learn-from-betters algorithm, $P\{\alpha' \leq 0\} = 0$, which means that at least one node changes its aggression level in each time slot. The probability that a node keeps its aggression level unchanged when the Learn-from-the-best algorithm is used is larger than that when the Learn-from-betters algorithm is used. We now elaborate on this observation. When the Learn-from-the-best algorithm is used, as the total number of nodes increases, the probability that a node keeps its aggression level unchanged increases. For the Learn-from-the-best algorithm, based on Theorem 1, the aggression level of a node increases only if a specific node is the winner in two consecutive time slots. As the total number of nodes increases, the probability that a node has the largest data transmission rate at two consecutive time slots decreases. In contrast, when the Learn-from-betters algorithm is used, the node that has the largest transmission rate in a time slot will increase its aggression level. We have also found that when the Learn-from-the-best algorithm is used, nodes change their aggression less frequently but the average amount of a change is larger. In contrast, when the Learn-from-betters algorithm is used, nodes change their aggression levels more frequently

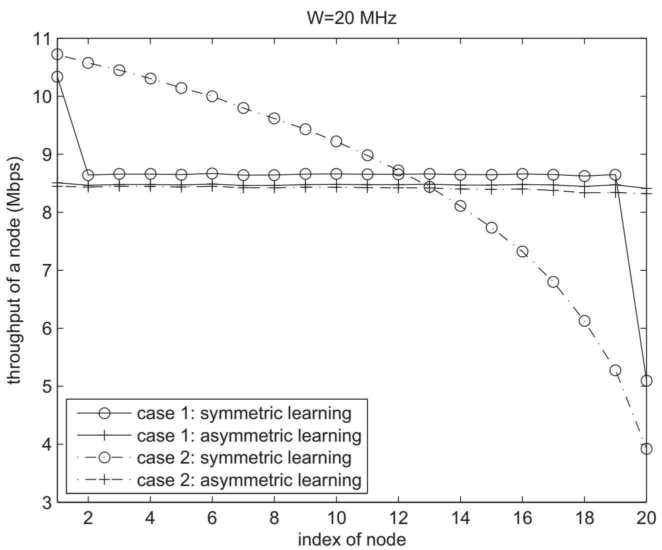

Fig. 9. Throughput distribution in an asymmetric network.

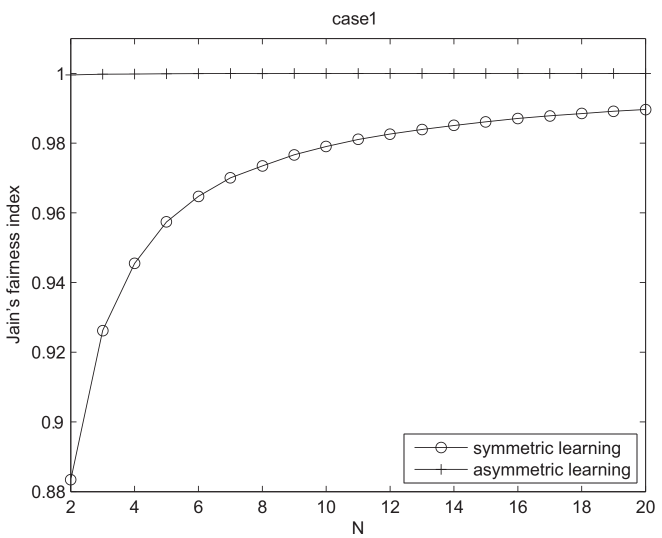

Fig. 10. Jain's fairness index for the proposed learning algorithms.

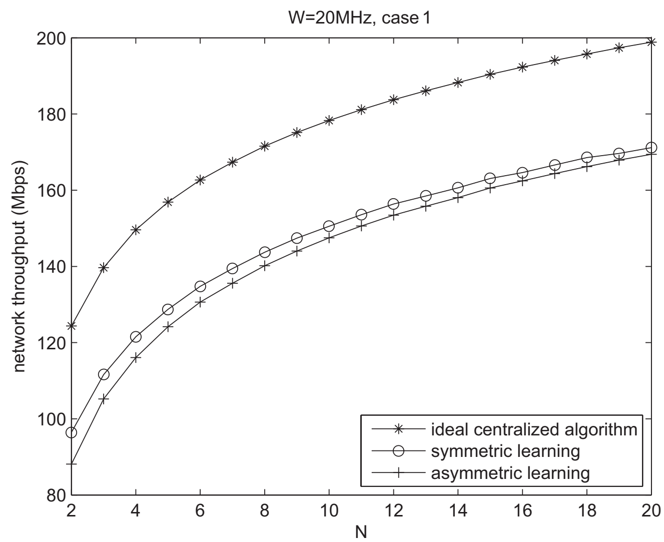

Fig. 11. Throughput in an asymmetric network.

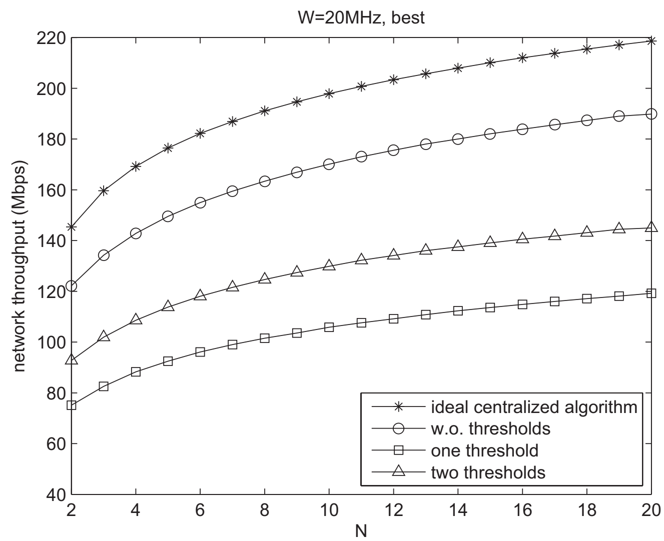

Fig. 12. Throughput when there are a finite number of available transmission rates

but the average amount of a change is smaller.

Figure 9 shows the throughput of each node in two networks when either the symmetric learning algorithm or the asymmetric learning algorithm is used. Case 1 corresponds to the first network, while case 2 corresponds to the second network. In case 1, the mean channel gains of node 1 and node N are set to 1.0 and 0.1, respectively. The mean channel gain of each of the other nodes is set to 0.5. In case 2, the mean channel gain of node i is set to $\frac{1}{i}, \forall 1 \leq i \leq N$. When the symmetric learning algorithm is used, the throughput of a node depends on its relative channel quality (in terms of the average channel gain) in the network. In contrast, when the asymmetric learning algorithm is used, the throughput of a node is independent of its relative channel quality in the network. It is due to that when the asymmetric learning algorithm is used, a node sets its initial value of aggression level based on its relative channel quality in the network.

In Figure 10, we show Jain's fairness index [34] when either the symmetric learning algorithm or the asymmetric learning algorithm is used in the first network mentioned above. As expected, regardless of the total number of nodes in the network, the fairness index of the asymmetric learning algorithm is larger than that of the symmetric learning algorithm. Figure 11 shows the network throughput for the symmetric learning algorithm, the asymmetric learning algorithm, and the ideal centralized algorithm. Note that the ideal centralized algorithm is only used to obtain an upper bound for the throughput performance of distributed algorithms. We can see that the throughput of the asymmetric learning algorithm is slightly lower than that of the symmetric learning algorithm. The symmetric learning algorithm is designed to maximize the network throughput and does not take fairness into consideration. On the other hand, the asymmetric learning algorithm is designed to strike a good balance between throughput and fairness.

In Figure 12, we show the impacts of the total number of

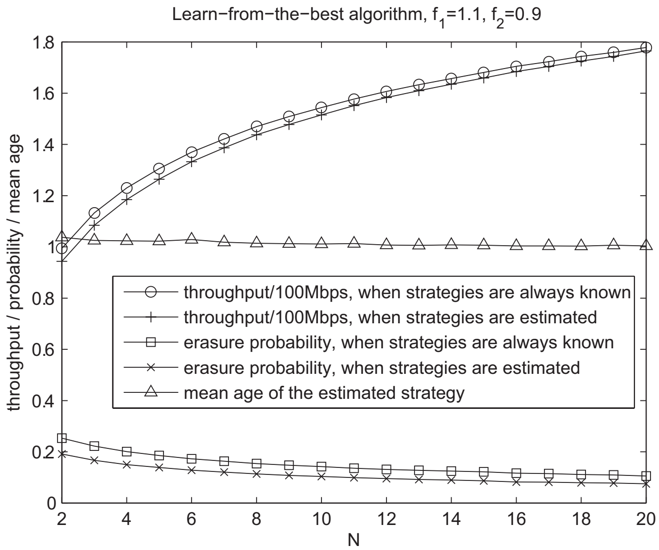

Fig. 13. The impacts of strategy estimation on the network throughput

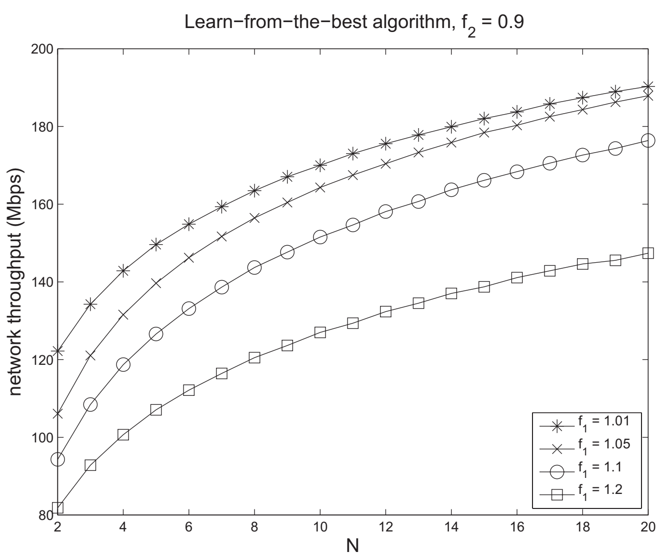

Fig. 14. The impacts of f_1 on the network throughput

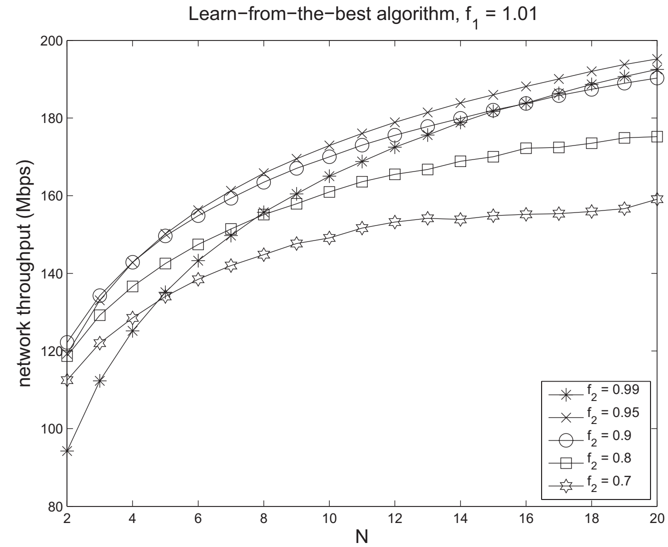

Fig. 15. The impacts of f_2 on the network throughput

available transmission rates on the network throughput. In the figure, the total number of thresholds corresponds to the total number of available transmission rates. When the total number of available transmission rates is not explicitly stated, all positive real numbers are available transmission rates. When the total number of available transmission rates is finite, we use the algorithm in Section VI to determine the near-optimal values for the available transmission rates. As expected, as the total number of available transmission rates increases, the network throughput increases. When there is only one available transmission rate, the corresponding throughput is about 53.89% of the ideal centralized algorithm. When there are two available transmission rates for a node to select, the associated throughput is about 66.32% of the ideal centralized algorithm. When system complexity is a primary concern, we could use the proposed learning algorithms with a few number of available transmission rates.

In Figure 13, we show the impacts of strategy estimation on the network throughput and the erasure probability, when $x_i(0) = 0$ and $\alpha_i(0) = 0.1$, $\forall i$. The erasure probability is the probability that none of the nodes successfully transmit data to the AP in a time slot. The strategy estimation algorithm works as follows. Let $\xi(i, t)$ be the last time up to time t when the access point successfully received data from node i. If there is no collision at time t, each node knows the current strategies used by all active nodes in the network. On the other hand, if a collision occurs at time t, node j treats the strategy used by node i at time $\xi(i, t)$ as the strategy used by node i at time t. In this case, the age of the estimated strategy for node i at time t is defined to be $t - \xi(i, t)$. We find that the network throughput when strategy estimation is used is slightly smaller than the network throughput when the strategies are always known. Meanwhile, the erasure probability when strategy estimation is used is also smaller than that when the strategies are always known. When strategies are always known, nodes increase their aggression levels too fast and therefore the erasure probability is larger. The figure also shows that the mean age of the estimated strategy is approximately one. This means the quality of strategy estimation is quite good. With a good strategy estimation algorithm, not always knowing the strategies does not lead to a significant decrease in the network throughput.

In Figure 14, we show the impacts of f_1 on the network throughput. As f_1 increases from 1.01 to 1.2, the network throughput decreases. When f_1 is too large, nodes increase their transmission rates too aggressively and therefore the updated rate vector becomes outside the capacity region. In Figure 15, we show the impacts of f_2 on the network throughput. As f_2 increases from 0.7 to 0.9, the network throughput increases. In contrast, as f_2 increases from 0.95 to 0.99, the network throughput decreases.

VIII. Conclusions

We have proposed capacity-region-aware learning algorithms for medium access control in wireless networks. The proposed algorithms explicitly take into consideration the information-theoretic capacity region of a multiple access channel. When the proposed algorithms are used, a node continuously tunes its strategy based on the previous strategies of other nodes and the channel feedback. A strategy is composed of two parts. The first part is the transmission threshold, while the second part is the aggression level. We have proposed symmetric learning algorithms to maximize the network throughput. In addition, we have proposed asymmetric learning algorithms to strike a good balance between throughput and fairness. Furthermore, we have studied the case in which the total number of available transmission rates is finite and proposed a novel scheme to determine the values of the available transmission rates. We have found that the network throughput depends on the initial value of the transmission threshold. In particular, in our study, the optimal value of the transmission threshold is zero. In contrast, since the aggression levels are dynamically adjusted, the network throughput is almost independent of the initial values of aggression levels. We have used analytical results and simulation results to justify the usage of the proposed medium access control algorithms. Future work includes dynamically adjusting the transmission threshold and the aggression level based on the current queue size. Another promising direction of future research is dynamically tuning both the aggression level and the transmission power to further improve the system performance. Modifying the proposed learning algorithms based on game theory and/or mechanism design to guarantee that selfish nodes will not misbehave is also an interesting topic of future research. Optimizing the parameters in the proposed learning algorithms based on the total number of nodes and the characteristics of wireless channels remains an open problem for future research.

APPENDIX

Theorem 1: For the Learn-from-the-best algorithm, if $\zeta(t) = \zeta(t+1) = 1$ and $w(t) = w(t+1)$, $\alpha_i(t+2) > \alpha_i(t+1), \forall i$.

Proof:

1. Since $\zeta(t) = \zeta(t+1) = 1$ and $w(t) = w(t+1)$, there exists an integer i such that $i = w(t) = w(t+1)$. Then, based on the Learn-from-the-best algorithm, we have $\alpha_j(t+1) = \alpha_i(t)$, $\forall j \neq i$, $\alpha_i(t+1) = \alpha_i(t) \cdot f_1$, $\alpha_j(t+2) = \alpha_i(t+1)$, $\forall j \neq i$, and $\alpha_i(t+2) = \alpha_i(t+1) \cdot f_1$.

2. Then, $\alpha_j(t+2) = \alpha_i(t+1) = \alpha_i(t) \cdot f_1 > \alpha_i(t) = \alpha_j(t+1), \forall j \neq i$. Namely, $\alpha_j(t+2) > \alpha_j(t+1)$, $\forall j \neq i$.

3. Similarly, $\alpha_i(t+2) = \alpha_i(t+1) \cdot f_1 = \alpha_i(t) \cdot (f_1)^2 > \alpha_i(t) \cdot f_1 = \alpha_i(t+1)$. Namely, $\alpha_i(t+2) > \alpha_i(t+1)$.

4. Based on 2 and 3, we have completed the proof.

QED.

Theorem 2: When either the Learn-from-the-best algorithm or the Learn-from-betters algorithm is used, if $x_i(0) = 0$, $\forall i$, $\alpha'(t) > 0$, $\forall t$.

Proof:

1. Since $x_i(0) = 0$, $\forall i$, $\zeta(t) \in \{1, 2\}$.

2. When $\zeta(t) = 1$, $\alpha_{w(t)}(t+1) = f_1 \cdot \alpha_{w(t)}(t)$. Thus, $\alpha'(t) = \frac{1}{N}[\sum_{i \neq w(t)} |\alpha_i(t+1) - \alpha_i(t)| + (f_1 - 1) \cdot \alpha_{w(t)}(t)]$. Since $(f_1 - 1) \cdot \alpha_{w(t)}(t) > 0$, $\alpha'(t) > 0$.

2. When $\zeta(t) = 2$ and the Learn-from-the-best algorithm is used, $\alpha_i(t+1) = f_2 \cdot \min_{j:j \in A(t)} \alpha_j(t), \forall i$. Thus, $\alpha'(t) = \frac{1}{N} \sum_{i=1}^{N} |f_2 \cdot \min_{j:j \in A(t)} \alpha_j(t) - \alpha_i(t)|$. Since $f_2 \cdot \min_{j:j \in A(t)} \alpha_j(t) < \alpha_i(t), \forall i$, $\alpha'(t) > 0$.

3. When $\zeta(t) = 2$ and the Learn-from-betters algorithm is used, $\alpha_i(t+1) = f_2 \cdot \bar{\alpha}(t), \forall i$. Thus, $\alpha'(t) = \frac{1}{N} \sum_{i=1}^{N} |f_2 \cdot \bar{\alpha}(t) - \alpha_i(t)|$. It is impossible that $\alpha_i(t) = f_2 \cdot \bar{\alpha}(t), \forall i$. Therefore, $\alpha'(t) > 0$.

4. Based on 2, 3, 4, we have completed the proof.

QED.

Theorem 3: $f(R_2)$ has one root in $[0, W \log_2 \frac{P}{\lambda\sigma^2 \ln 2}]$, if $\frac{P}{\lambda\sigma^2 8 \ln 2} > 1$.

Proof:

1. Since $0 < 2^{-\frac{P}{\lambda\sigma^2 \ln 2}} < 1$, $e^{-\frac{\lambda\sigma^2}{P}(2^{-\frac{P}{\lambda\sigma^2 \ln 2}} - 1)} > 1$. Therefore, $f(0) = 1 - e^{-\frac{\lambda\sigma^2}{P}(2^{-\frac{P}{\lambda\sigma^2 \ln 2}} - 1)}(1 + 2^{-\frac{P}{\lambda\sigma^2 \ln 2}}) < 1 - 1(1+0) = 0$. Thus, $f(0) < 0$.

2. Since $\frac{P}{8\lambda\sigma^2 \ln 2} > 1$, $\log_2 \frac{8\lambda\sigma^2 \ln 2}{P} < 0$. In addition, $e^{-x} > 0$, $\forall x$. Therefore, $f(W \log_2 \frac{P}{\lambda\sigma^2 \ln 2}) = e^{-\frac{\lambda\sigma^2}{P}(\frac{P}{\lambda\sigma^2 \ln 2} - 1)} - \frac{1}{2} e^{-\frac{\lambda\sigma^2}{P}(\frac{P}{2\lambda\sigma^2 \ln 2} - 1)} \times \log_2 \frac{8\lambda\sigma^2 \ln 2}{P} > 0 + \frac{1}{2} \cdot 0 \cdot 0 = 0$. Thus, $f(W \log_2 \frac{P}{\lambda\sigma^2 \ln 2}) > 0$.

3. Based on Equation (23), the function f is a continuous function in $(0, \infty)$.

4. Based on 1, 2, and the theorem of intermediate value for continuous functions, the continuous function f has one root in $[0, W \log_2 \frac{P}{\lambda\sigma^2 \ln 2}]$.

QED.

REFERENCES

[1] T. M. Cover and J. A. Thomas, *Elements of Information Theory*, 2nd ed. John Wiley and Sons, 2006.

[2] Q. Zhao and L. Tong, “A multiqueue service room MAC protocol for wireless networks with multipacket reception,” *IEEE/ACM Trans. Netw.*, vol. 11, no. 1, pp. 125–137, Feb. 2003.

[3] G. D. Celik, G. Zussman, W. F. Khan, and E. Modiano, “MAC for networks with multipacket reception capability and spatially distributed nodes,” *IEEE Trans. Mobile Comput.*, vol. 9, no. 2, pp. 226–240, Feb. 2010.

[4] Y. He, J. Sun, X. Ma, A. V. Vasilakos, R. Yuan, and W. Gong, “Semi-random backoff: towards resource reservation for channel access in wireless LANs,” *IEEE/ACM Trans. Netw.*, vol. 21, no. 1, pp. 204–217, Feb. 2013.

[5] G. Hauksson and M. Alanyali, “Wireless medium access via adaptive backoff: delay and loss minimization,” in *Proc. 2008 IEEE INFOCOM*, pp. 1777–1785.

[6] J. W. Lee, M. Chiang, and A. R. Calderbank, “Utility-optimal random-access control,” *IEEE Trans. Wireless Commun.*, vol. 6, no. 7, pp. 2741–2751, July 2007.

[7] A. H. Mohsenian-Rad, J. W. Huang, M. Chiang, and V. W. S. Wong, “Utility-optimal random access: reduced complexity, fast convergence, and robust performance,” *IEEE Trans. Wireless Commun.*, vol. 8 no. 2, pp. 898–911, Feb. 2009.

[8] A. H. Mohsenian-Rad, J. W. Huang, M. Chiang, and V. W. S. Wong, “Utility-optimal random access without message passing,” *IEEE Trans. Wireless Commun.*, vol. 8, no. 3, pp. 1073–1079, Mar. 2009.

[9] J. S. Lin and K. T. Feng, “QoS-Based adaptive contention/reservation medium access control protocols for wireless local area networks,” *IEEE Trans. Mobile Comput.*, vol. 10, no. 12, pp. 1785–1803, Dec. 2011.

[10] X. Wang and K. Kar, “Cross-layer rate optimization for proportional fairness in multihop wireless networks with random access,” *IEEE J. Sel. Areas Commun.*, vol. 24, no. 8, pp. 1548–1559, Aug. 2006.

[11] D. Zheng, M. O. Pun, W. Y. Ge, J. S. Zhang, and H. V. Poor, “Distributed opportunistic scheduling for ad hoc communications with imperfect channel information,” *IEEE Trans. Wireless Commun.*, vol. 7, no. 12, pp. 5450–5460, Dec. 2008.

[12] J. Eshet and B. Liang, “Randomly ranked mini slots for fair and efficient medium access control in ad hoc networks,” *IEEE Trans. Mobile Comput.*, vol. 6, no. 5, pp. 481–493, May 2007.

[13] Y. Su and M. van der Schaar, "Dynamic conjectures in random access networks using bio-inspired learning," *IEEE J. Sel. Areas Commun.*, vol. 26, no. 7, pp. 1116–1127, 2010.

[14] J. B. Seo and V. C. M. Leung, "Design and analysis of cross-layer contention resolution algorithms for multi-packet reception slotted ALOHA systems," *IEEE Trans. Wireless Commun.*, vol. 10, no. 3, pp. 825–833, Mar. 2011.

[15] P. Minero and M. Franceschetti, "Throughput of slotted ALOHA with encoding rate optimization and multipacket reception," in *Proc. 2009 IEEE INFOCOM*, pp. 2971–2975.

[16] M. F. Guo, X. B. Wang, and M. Y. Wu, "On the capacity of K-MPR wireless networks," *IEEE Trans. Wireless Commun.*, vol. 8, no. 7, pp. 3878–3886 July 2009.

[17] R. H. Gau, "Performance analysis of slotted Aloha in interference dominating wireless ad-hoc networks," *IEEE Commun. Lett.*, vol. 10, no. 5, pp. 402–404, May 2006.

[18] R. H. Gau, "Performance analysis of finite-user slotted Aloha in wireless networks with multipacket reception and random traffic," *IEEE Commun. Lett.*, vol. 12, no. 2, pp. 140–142, Feb. 2008.

[19] A. Dua, "Random access with multi-packet reception," *IEEE Trans. Wireless Commun.*, vol. 7, no. 6, pp. 2280–2288, June 2008.

[20] R. Yim, N. B. Mehta, A. F. Molisch, and J. Y. Zhang, "Dual power multiple access with multipacket reception using local CSI," *IEEE Trans. Wireless Commun.*, vol. 8, no. 8, pp. 4078–4088 Aug. 2009.

[21] W. L. Huang, K. B. Letaief, and Y. J. Zhang, "Joint channel state based random access and adaptive modulation in wireless LANs with multi-packet reception," *IEEE Trans. Wireless Commun.*, vol. 7, no. 11, pp. 4185–4197, Nov. 2008.

[22] R. H. Gau, "Modeling the slotted nonpersistent CSMA protocol for wireless access networks with multiple packet reception," *IEEE Commun. Lett.*, vol. 13, no. 10, pp 797–799, Oct. 2009.

[23] R. H. Gau and K. M. Chen, "Probability models for the splitting algorithm in wireless access networks with multi-packet reception and finite nodes," *IEEE Trans. Mobile Comput.*, vol. 7, no. 12, pp. 1519–1535, Dec. 2008.

[24] R. H. Gau, "Tree/stack splitting with remainder for distributed wireless medium access control with multipacket reception," *IEEE Trans. Wireless Commun.*, vol. 10, no. 11, pp. 3909–3923, Nov. 2011.

[25] T. Cui, L. Chen, and S. H. Low, "A game-theoretic framework for medium access control," *IEEE J. Sel. Areas Commun.*, vol. 28, no. 4, pp. 587–601, Sept. 2008.

[26] Y. Jin and G. Kesidis, "Distributed contention window control for selfish users in IEEE 802.11 wireless LANs," *IEEE J. Sel. Areas Commun.*, vol. 25, no. 6, pp. 1113–1123, Aug. 2007.

[27] H. Inaltekin and S. B. Wicker, "The analysis of Nash equilibria of the one-shot random-access game for wireless networks and the behavior of selfish nodes," *IEEE/ACM Trans. Netw.*, vol. 16, no. 5, pp. 1094–1107, Oct. 2008.

[28] L. J. Chen, S. H. Low, and J. C. Doyle, "Random access game and medium access control design," *IEEE/ACM Trans. Netw.*, vol. 18, no. 4, pp. 1303–1316, Aug. 2010.

[29] Y. G. Cho, C. S. Hwang, and F. A. Tobagi, "Design of robust random access protocols for wireless networks using game theoretic models," in *Proc. 2008 IEEE INFOCOM*, pp. 1750–1758.

[30] P. Nuggehalli, M. Sarkar, K. Kulkarni, and R. R. Rao, "A game-theoretic analysis of QoS in wireless MAC," in *Proc. 2008 IEEE INFOCOM*, pp. 1903–1911.

[31] K. Akkarajitsakul, E. Hossain, D. Niyato, and D. I. Kim, "Game theoretic approaches for multiple access in wireless networks: a survey," *IEEE Commun. Surveys Tuts.*, vol. 13, no. 3, pp. 372–395, 3rd Quarter 2011.

[32] C. W. Tan, M. Chiang, and R. Srikant, "Fast algorithms and performance bounds for sum rate maximization in wireless networks," *IEEE/ACM Trans. Netw.*, vol. 21, no. 3, pp. 706–719, June 2013.

[33] R. L. Burden and J. D. Faires, *Numerical Analysis*, 7th ed. Wadsworth Group, 2001.

[34] R. Jain, D. Chiu, and W. Hawe, "A quantitative measure of fairness and discrimination for resource allocation in shared systems," Digital Equipment Corporation, DEC-TR-301, Tech. Rep., 1984. Available: http://www.cse.wustl.edu/$\sim$jain/papers/fairness.htm

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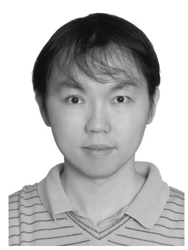

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