Throughput Improvement of 802.11 Networks via Randomization of Transmission Power Levels

Mingrui Zou, Sammy Chan, *Member, IEEE*, Hai L. Vu, *Senior Member, IEEE*, and Li Ping, *Fellow, IEEE*

***Abstract*—Successive interference cancellation can resolve collisions involving multiple packets and hence improve the throughput of an 802.11 network. This technique, however, requires packets to be sent with different power levels. In this paper, we first develop a detailed analytical model to determine the throughput of 802.11 networks with this multiple-packet reception capability. We then study the problem of determining the optimal probability distribution associating with these power levels when the network is operated in infrastructure and ad-hoc modes, respectively. In the infrastructure mode, the problem is formulated as an optimization problem with solution to be broadcasted to all the nodes by the access point. In the ad-hoc mode, the same problem is formulated as a mixed strategy game where individual node strategically chooses the probability distribution of the transmitting power levels so to maximize its own throughput. We show that the Nash equilibrium of this game is Pareto optimal and fair. Furthermore, the resulting throughput of the distributed approach is close to the optimal performance of the infrastructure mode.**

***Index Terms*—power randomization, multiple-packet reception, 802.11, game-theoretic.**

I. Introduction

A wireless local area network (WLAN), regulated by the IEEE 802.11 standards, is a shared medium network that provides wireless Internet access to mobile devices. Since its inception, WLAN and its variants have attracted a lot of interests in both research communities and the commercial world and become one of the most deployed networks on earth [1].

In IEEE 802.11 WLANs, a so-called contention-based distributed coordination function (DCF) is a basic mechanism controlling the access of the wireless shared medium. The DCF mechanism is based on a carrier sense multiple access with collision avoidance (CSMA/CA) protocol. In particular, if more than one station transmits packets at the same time, a collision happens and the retransmissions of the collided packets are managed according to the binary exponential backoff schedule.

Collisions result in packet loss in the traditional 802.11 DCF scheme. However, it is possible to resolve collisions and successfully decode multiple packets. This is referred to as multiple packet reception (MPR). The conventional MPR techniques are mostly discussed for single-user-detection systems [2]-[4], which can achieve low information rate only.

There have been various multi-user-detection techniques proposed, including zero-forcing, minimum-mean-square-error, maximum likelihood, parallel interference cancellation and successive interference cancellation (SIC) methods [5]. Recently, a SIC-based MPR scheme that can be applied to high rate applications is developed in [6]. In this scheme (referred to as SIC with power randomization (SPR)), each user chooses its transmission power randomly, which increases the probability of recovering the signals during a collision. The focus of [6] is to prove that the optimal support for this distribution is a discrete set, which greatly simplifies the optimization problem involved. For an idealized ALOHA networks, it is shown in [6] that SPR can significantly improve the network throughput but only by using a *properly designed* power distribution. For more practical and popular IEEE 802.11 WiFi networks (i.e. WLANs), however, obtaining an optimal power distribution to achieve this same throughput improvement is a non-trivial task. It is because the effect of a power randomization is greatly influenced by the so-called carrier sense multiple access (CSMA) based collision detection and retransmission mechanisms defined in the IEEE 802.11 access protocol standard for WLANs. This paper attempts to fill this gap via the development of a novel optimization framework based on stochastic and game approaches for both the infrastructure and ad-hoc WLAN, respectively. To this end, the contributions of this paper are:

- We propose a framework for the optimal design of the probability mass function (PMF) of the transmission power to maximize throughput in both the infrastructure and ad-hoc network settings.
- For infrastructure mode, we provide a new algorithm that jointly determines the fixed point solution for the attempt probability of an arbitrary node while finding the optimal PMF of its transmission power to maximize the overall MAC throughput. Various scenarios are treated over both ideal and fading channels with and without power budget constraint.
- For ad-hoc mode, we develop a novel game model to analyze the behavior and power selection strategy of

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M. Zou is with China Academy of Engineering Physics, Mianyang, China (e-mail: mingruizou@foxmail.com).

S. Chan and Li Ping are with the Department of Electronic Engineering, City University of Hong Kong, Hong Kong SAR, P.R.China (e-mail: {eeschan,eeliping}@cityu.edu.hk).

H.L. Vu is with Faculty of Science, Engineering & Technology, Swinburne University of Technology, P.O. Box 218, VIC 3122, Australia (e-mail: h.vu@ieee.org).

selfish nodes operating in an ad-hoc mode. Contrary to the expectations, our findings suggest that the Nash equilibrium in the ad-hoc mode is actually Pareto optimal that is very close to what can be optimally achieved in the infrastructure mode but without any centralized coordination. To our knowledge, this is the first time that optimal design of MPR is addressed, and in both operating modes of the 802.11 networks.
- As par of the proposed optimization framework, a detailed stochastic model of the 802.11 DCF with MPR is developed to obtain an accurate expression of the MAC layer throughput. We show via simulation that our analytical formulae are very accurate. Significantly, we also find the closed relationship between the power randomization and the resulting improvement in throughput.

The rest of the paper is organized as follows. In Section II, earlier works on the impact of MPR on the MAC layer are reviewed. In Section III, the SPR scheme is introduced. In Section IV, the analytical model of an unsaturated IEEE 802.11 DCF network operating SPR in the physical layer is developed and the accuracy of the model is validated through simulations. In Section V, throughput optimization for a network in infrastructure mode is investigated. In Section VI, a mixed-strategy game model is proposed for a network operating in ad hoc mode. The resulting Nash equilibrium probability distribution of power levels is then investigated and discussed. Finally, Section VII concludes the paper.

II. Related Work

The provision of MPR raises two important research questions [7]. How does the MPR capability affect the MAC protocol performance and how to design a suitable protocol to fully utilize the MPR capability? There have been much literature focused on modeling the random access networks with MPR capability. In [8] and [9], a model for general MPR channels was proposed and the performance for slotted ALOHA with infinite-user assumption was analyzed. It was extended to a finite-user ALOHA system in [10]. Moreover, the multiacccess theory on MPR channels developed in [8] and [9] was significantly extended to CSMA protocols in [11]. In [12] and [7], the protocols to exploit the MPR capability were proposed. The Multi-Queue Service Room protocol was introduced in [12] which could yield the optimal utilization of the MPR channel, but with the drawback of high computational complexity. In [7], a much simpler protocol with comparable performance to that of Multi-Queue Service Room protocol was proposed. In [13], a multi-round contention random-access protocol is proposed to improve the capacity of MPR-enabled WLANs. In [14], the effect of MPR on the MAC layer collision resolution schemes was studied. It was shown that the widely used binary exponential backoff scheme did not yield close-to-optimal network throughput for both non-carrier-sensing networks and carrier-sensing networks operating in the basic access mode.

The use of random transmission power to improve the throughput of slotted ALOHA systems with power capture effect were studied in [3] and references therein. These work investigated the optimal choice of power levels and the associated transmit probabilities under various capture models which support single user detection. To fully utilize the MPR capability, in [15], the authors proposed a power control scheme to solve the inefficiency of using the MPR channel in multi-rate wireless networks which supports variable packet length. The power level of nodes in the proposed scheme is either increased or decreased according to their transmission durations.

Recently, Patras *et al.* propose a power-hopping scheme to improve the throughput of 802.11 networks [16]. According to the scheme, transmission power levels are alternated periodically to enable packet capture at the receiver. As a result, the impact of collisions is reduced and the throughput performance of all stations is improved. They have demonstrated that significant throughput improvement can be gained in an experimental testbed. However, different from our work, they only consider infrastructure mode and their focus is not about how to determine the optimal power profile. Moreover, they do not take into account the constraint of average transmission power.

III. SIC with Power Randomization

A. AWGN Channels

Consider a 2-user non-fading multiple-access channel. The received signal y can be represented by

$$y = \sum_{i=1}^{2} \sqrt{e_i} x_i + n \tag{1}$$

where x_i is the transmitted signal of user i (here $i = 1, 2$) with power normalized to 1, e_i is power level used to transmit x_i, and n is the complex Gaussian noise with mean 0 and variance N_0. We assume that each user transmits at a fixed rate R (bit/symbol). Consider that SIC is deployed in the receiver. Assume that user 1 is decoded first where the signal of user 2 is regarded as the noise. For reliable transmission, the following constraint is required [17],

$$\log_2 \left(1 + \frac{e_1}{e_2 + N_0}\right) \geq R. \tag{2}$$

Upon successful decoding, signal of user 1 is subtracted from y. Then the information for user 2 can be successfully decoded from the residual signal after substraction provided that,

$$\log_2 \left(1 + \frac{e_2}{N_0}\right) \geq R. \tag{3}$$

Similar discussions can be given to the situation with user 2 being decoded first. Note that the situation with $e_i = 0$ means user i is not transmitting and so there is no collision. We will regard this as a successful case.

Based on the constraints in (2) and (3), a transmission strategy can be designed as follows. Let E_i be a positive real value recursively defined below,

$$E_i = \begin{cases} 0 & i = 0, \\ (2^R - 1)(E_{i-1} + N_0) & i = 1, 2, 3, \dots \end{cases} \tag{4}$$

Observe that $E_{i+1} > E_i$ ($\forall i > 1$). According to [6], the discrete power set $\mathcal{E}$ is defined as

$$\mathcal{E} = \begin{cases} \{E_1, \cdots, E_Q\} & R < 1, \\ \{E_1, \cdots, E_i, \cdots\} & R \geq 1, \end{cases} \tag{5}$$

where E_Q is the solution of the equation $E_Q = (2^R - 1)(E_Q + N_0)$.

The set $\mathcal{E}$ has the following two properties.

Property (i): For $i > j$, E_i and E_j satisfy (2), i.e.,

$$\log_2 \left(1 + \frac{E_i}{E_j + N_0}\right) \geq R. \tag{6}$$

Property (ii): For any $j > 0$, E_j satisfies (3), i.e.,

$$\log_2 \left(1 + \frac{E_j}{N_0}\right) \geq R. \tag{7}$$

Now let the power level of each of users 1 and 2 be randomly drawn from $\mathcal{E}$. According to Properties (i) and (ii), when two users are transmitting simultaneously, as long as their chosen power levels are different, both of their signals can be successfully decoded.

It has been proved in [6] that (5) gives an optimal power profile based on which the achieved throughput is not worse than any other profile while less average power is consumed. In Sections V and VI, based on this optimal power profile, we will derive the optimal PMF for those discrete power levels in $\mathcal{E}$ in order to maximize the system throughput.

B. Fading Channels

For the case of fading channels, the received signal y of a N-user system can be represented by

$$y = \sum_{i=1}^{N} \sqrt{g_i}\sqrt{e_i}x_i + n, \tag{8}$$

where g_i is the channel gain of user i. Here, it is assumed that the channel gain of each user is independent and identically distributed. Therefore, $g_i = g, \forall i$.

Recall from the previous subsection that the optimal power levels at the receiver should be $\{E_1,\ E_2,\ \ldots\ E_M\}$ as given by (4). Therefore, we need to adjust the power levels at the transmitter according to the channel condition to achieve this. Assuming that nodes have perfect channel state information, i.e, when a node transmits, the instantaneous channel gain g is known. This is possible when the channel is reciprocal; each node can measure g from the received signal sent by its communication peer. Then, for a given g, the optimal power levels at the transmitter are $\{E_1/g,\ E_2/g,\ \ldots\ E_M/g\}$. In addition, according to our power randomization approach, a channel gain g is associated with a PMF $p_i(g)$, $i = 1, 2, \ldots, M$, where $p_i(g)$ denotes the probability that a node transmits with power $\frac{E_i}{g}$ given that it transmits.

Let $\Psi(g)$ be the probability density function of g. Hence, at the receiver, the distribution of received power $f_R(e_R)$ is given by

$$f_R(e_R) = \sum_{i=1}^{M} p_i \delta(e_R - E_i), \tag{9}$$

where

$$p_i = \int p_i(g)\Psi(g)dg,\ i = 1, 2, \ldots, M. \tag{10}$$

C. Impact of Power Randomization

The following comparison between systems with and without power randomization provides useful insights about SPR.

For simplicity, let us first consider a two-user system without power randomization. We consider that the transmission power of each user is the same and the arrival power is denoted as E. In the case of a collision, the received signal-to-interference-noise ratio (SINR) is given by:

$$SINR^{(1)} = SINR^{(2)} = \frac{E}{E + N_0}. \tag{11}$$

For simplicity, we assume ideal coding. Then the Shannon formula becomes

$$R \leq \log_2 \left(1 + \frac{E}{E + N_0}\right), \tag{12}$$

where R is the information rate for each user.

Equation (12) implies that a feasible E can be found only when $R \leq 1$, so a collision is not resolvable if $R > 1$. This is the reason that the work in [2]-[4] on MPR are for on low-rate CDMA applications. Note that this is the consequence of the restriction that there is only one level of arrival power in (11). Otherwise, if there are multiple levels of arrival powers for the two users, $R > 1$ is feasible by SIC, as discussed in Section III-A.

IV. Throughput of DCF with SPR

A. Analytical Modeling

There have been many works on modeling DCF to evaluate performance at the MAC layer in IEEE 802.11 WLANs. For example, Bianchi [18] proposed a Markovian model to compute the throughput at the MAC layer of a saturated IEEE 802.11 WLAN. A non-saturated analytical model was proposed in [19] to extend Bianchi's model. Markovian models can provide high accuracy but could quickly become analytically untractable due to the large state space involved. In [20], based on renewal processes, the authors studied a fixed-point formulation to provide a simpler approach to analyze the performance of DCF in saturated IEEE 802.11 WLANs. By using the elements from the saturated model in [20], a simpler non-saturated model was proposed in [21] that has comparable accuracy to other existing non-saturated analytical models.

In this section, we extend the model in [21] to evaluate the throughput of the basic access mode of DCF with the capability of multiple packet reception enabled by SPR. Consider an unsaturated IEEE 802.11 network consisting of N nodes in an infrastructure mode. We assume that the channel is ideal. The minimum contention window and the retransmission limit used in DCF are denoted as W and K, respectively.

Let τ' be the attempt rate per slot given that a node has a packet to send and τ be the unconditional attempt rate per slot for each node. Also, let ρ be the utilization of a node (i.e. probability that a node has packets to send). Hence, we have

$$\tau = \rho\tau'. \tag{13}$$

Assuming that packets arrive at a node with rate λ (packet/second), and that each node has an infinite buffer. Each node can be modeled as an $G/G/1/\infty$ queue [21], with the service time being determined by the DCF protocol. Let $\overline{S}$ be the average service time, then

$$\rho = \lambda\overline{S}. \tag{14}$$

Thus the general expression for τ is given by

$$\tau = \min(1, \rho)\tau'. \tag{15}$$

where the *min()* function is used to prevent the probability of a nonempty buffer from exceeding one since the utilization cannot exceed one.

First, we need to find the expression for τ'. Let γ be the collision probability experienced by a tagged node, $R(\gamma)$ and $\overline{W}$ be the average number of attempts and the mean backoff time (in slots) till a packet transmission is finished (either successful or not), respectively. Denote by b_i the mean backoff duration (in slots) at the *i*th attempt, $0 \le i \le K$. With the binary exponential backoff, b_i is given by

$$b_i = \begin{cases} \frac{W}{2} & i = 0, \\ 2^i b_0 & 1 \le i \le m-1, \\ 2^m b_0 & m \le i \le K, \end{cases} \tag{16}$$

where m determines maximum backoff window size (i.e. $CW_{max} = 2^m W$). Then it is straightforward to obtain [20]

$$\begin{aligned} R(\gamma) &= 1 + \gamma + ... + \gamma^K, \\ \overline{W} &= b_0 + \gamma b_1 + ... + \gamma^K b_K. \end{aligned} \tag{17}$$

As in [20], τ' can be expressed as a ratio between $R(\gamma)$ and $\overline{W}$,

$$\tau' = \frac{R(\gamma)}{\overline{W}} = \frac{1 + \gamma + .. + \gamma^K}{b_0 + \gamma b_1 + .. + \gamma^K b_K}. \tag{18}$$

When accessing the channel, each node can select a power level from $\mathcal{E}$ to transmit its packets (i.e. MAC frame). With SPR, packets can be received successfully if there is no collision, or two packets are simultaneously transmitted at different power levels. Let p_i be the probability that a node chooses power level E_i given that it transmits. Thus, $\{p_i\}$ denotes the PMF of the power levels. The probability $P[E_i \neq E_j]$ that two nodes do not choose the same power levels is given by

$$P[E_i \neq E_j] = 1 - \sum_{i=1}^{M} p_i^2. \tag{19}$$

In the special case that power levels are uniformly distributed, then

$$P[E_i \neq E_j] = 1 - M(\frac{1}{M})^2 \tag{20}$$

where M is the number of non-zero power levels available.

Let P_b and P_s be the probability that a chosen slot is busy and that a packet transmission is successful given that there is an activity in that slot, respectively. We have

$$P_b = 1 - (1-\tau)^N \tag{21}$$

$$P_s = \frac{P_1 + P_2}{P_b} \tag{22}$$

where

$$P_1 = \binom{N}{1}\tau(1-\tau)^{N-1} \tag{23}$$

is the probability that there is only one packet transmitted in a slot, and

$$P_2 = \binom{N}{2}\tau^2(1-\tau)^{N-2}P[E_i \neq E_j] \tag{24}$$

is the probability that two packets are simultaneously transmitted in a single slot but with different power levels.

To calculate $\overline{S}$ in (14), first we determine the length of the virtual slot time T_v (in seconds) which is the mean time that elapses for one decrement of the backoff counter. Considering that, with probability $1 - P_b$, the slot time is idle (with duration denoted as σ); with probability P_bP_s, it contains a successful transmission (with duration denoted as T_s), and with probability $P_b(1 - P_s)$ it contains a collision (with duration denoted as T_c). Thus, the virtual slot time T_v is given by [21]

$$T_v = (1-P_b)\sigma + P_bP_s(T_s + \sigma) + P_b(1-P_s)(T_c + \sigma) \tag{25}$$

where

$$T_s = T_{data} + T_{SIFS} + T_{ACK} + T_{DIFS} \tag{26}$$

and

$$T_c = T_{data} + T_{timeout} + T_{DIFS} \tag{27}$$

and $T_{timeout} = T_{ACK} + T_{SIFS}$. Here, we assume that one single ACK packet can acknowledge two packets simultaneously. T_{data} denotes the transmission time of a data packet assumed to be the same for every node in the network, T_{ACK} is the transmission time of an ACK packet, T_{SIFS} and T_{DIFS} represent the duration of $SIFS$ and $DIFS$, respectively. The average service time $\overline{S}$ (in seconds) is then

$$\overline{S} = \overline{W}T_v. \tag{28}$$

Finally γ can be calculated as

$$\gamma = 1 - (1-\tau)^{N-1} - (N-1)\tau(1-\tau)^{N-2}P[E_i \neq E_j]. \tag{29}$$

Equations (15), (18) and (29) establish a fixed point from which γ can be numerically computed. The system throughput (in bit/second) is given by

$$T = \frac{LP_1 + 2LP_2}{T_v}, \tag{30}$$

where L is the packet size in bits.

For the case of fading channels, if $p_j(g)$ and the channel model are specified, p_j can be calculated by (10), and the throughput can be calculated using this model as well.

B. Validation

The model is verified by ns-2 version 2.29. The simulation parameters are listed in Table I. To simplify the simulation, the actual decoding process is omitted. In other words, two simultaneously arrived packets are regarded as decoded successfully if they are transmitted at different power levels. The system throughput is normalized by the data transmission rate R_{data}. And the normalized offered load is given by

$$l = \frac{N \lambda L_{pay}}{R_{data}} \tag{31}$$

where L_{pay} is the packet payload in bits.

TABLE I: Simulation parameters for ns-2

CWmin	32
CWmax	1024
Slot Time	20 us
SIFS	10 us
DIFS	50 us
Retry Limit	7
PHY header	192 bits
MAC header	224 bits
Route Header	20 bytes
ACK	112 bits + PHY header
Data bit rate	11 Mbps
Bit error rate	error free

For simplicity, we first study the performance of DCF with SPR under uniform distribution of discrete power levels, i.e., $P[E_i \neq E_j] = 1 - M(1/M)^2$. The packet payload is set to be 500 bytes. Fig. 1 plots the system throughput against offered load for various M and N. The accuracy of the proposed performance model is demonstrated by the agreement between the simulation and analysis results. Also included in the figure are the analytical performance results of the original 802.11 DCF protocol, labeled as "Basic Model Analysis (no SPR)". It can be seen that, with SPR, the system throughput has been significantly improved. For example, for the case of $M = 10$ and $N = 15$, the system throughput has been improved around 45% with SPR. More results with different M and N can be found in [22]. We also investigate the impact of M on the throughput improvement. From Fig. 2, it can be seen that when M increases from 3 to 10, system throughput increases. However, further increase in M only leads to negligible increase in throughput. This indicates that in practice, we do not need to have too many power levels.

Next, we evaluate the performance of DCF with SPR using arbitrary PMFs of power levels for the case of $M = 3$, $N = 5$. The arrival rate λ and the packet payload are set to be 250 pkts/sec and 500 bytes, respectively, which give the normalized offered load $l = 0.4545$. Fig. 3 plots the throughput against a set of power level PMFs in which each element represents a combination of probabilities of the three power levels. In Fig. 3, the x-axis starts with *Element 1* $(0, 0, 1.0)$, which means that the third power level is always chosen. The subsequent elements are obtained by changing the

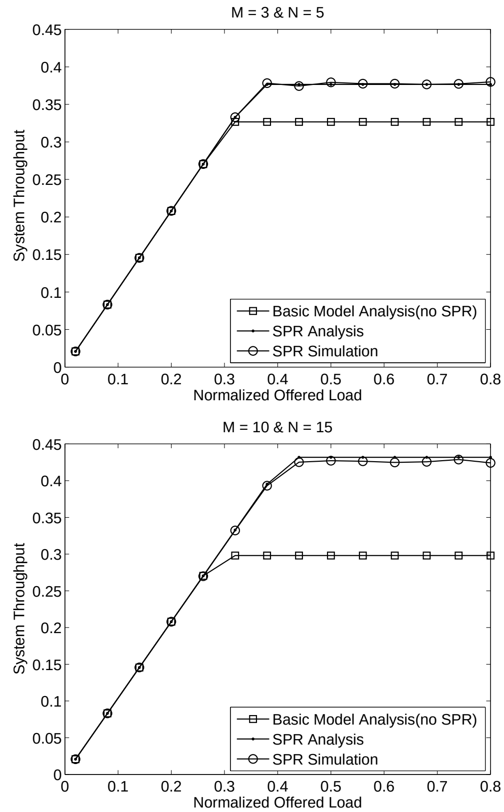

Fig. 1: System throughput versus normalized offered load for ($M = 3, N = 5$) and ($M = 10, N = 15$).

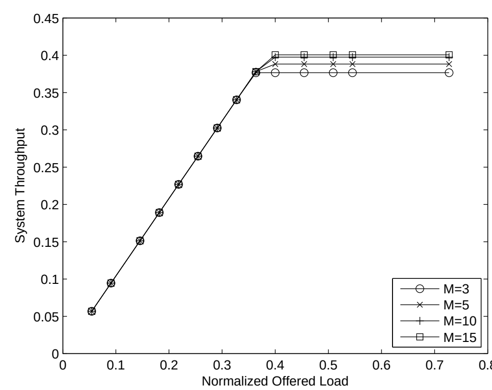

Fig. 2: System throughput versus normalized offered load for M = 3,5,10,15.

last two probabilities by a step size of 0.1 before increasing the first one by the same amount. For example, *Element 2, Element 3* and *Element 4* are $(0, 0.1, 0.9)$, $(0, 0.2, 0.8)$, $(0, 0.3, 0.7)$, respectively. Again, the accuracy of the proposed model is demonstrated by the agreement between the simulation and analysis results. As shown in Fig. 3, for those PMFs which are close to uniform distribution, e.g., $(0.3, 0.3, 0.4)$, $(0.3, 0.4, 0.3)$ and $(0.4, 0.3, 0.3)$, their resultant throughputs are close to that corresponding to the offered load of 0.4545 depicted in Fig. 1. More importantly, Fig. 3 shows that by choosing an appropriate PMF, the system throughput can be

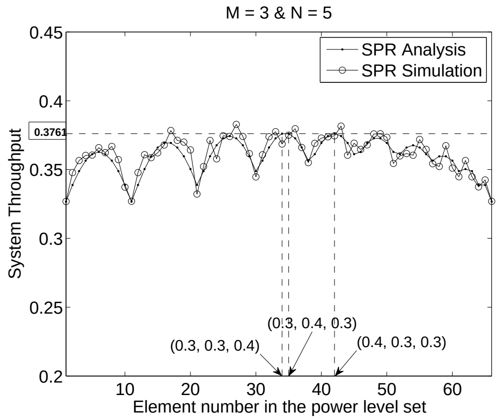

Fig. 3: System throughput versus PMFs of power levels for N = 5 and M = 3.

optimized. This will be studied in Section V next.

V. Throughput Optimization in Infrastructure Mode

In this section, we aim to find the optimal PMF of the discrete power levels used by each node to maximize the system throughput when the network is operated in the infrastructure mode.

A. Without Power Constraint

First, we consider a simple case in which there is no constraint of the average consumed power. From Section IV-A, the system throughput is given by (30). Accordingly, we define the following optimization problem

$$\begin{aligned} &\text{maximize} \quad L\frac{P_1+2P_2}{T_v} \\ &\text{such that} \quad \sum_{i=1}^{M} p_i = 1, \\ &\qquad\qquad\quad 0 \le p_i \le 1, \end{aligned} \tag{32}$$

where P_1, P_2, T_v are given in (23), (24) and (25), respectively. Substituting these equations into (30), the optimization objective function can be written as

$$T = LN\frac{\tau(1-\tau)^{N-1} + (N-1)\tau^2(1-\tau)^{N-2}(1-\sum_{i=1}^{M} p_i^2)}{\sigma + T_s[1-(1-\tau)^N]}. \tag{33}$$

In particular, to maximize the system throughput, we must maximize (33) with respect to the individual probabilities p_i subject to the specified constraints.

The resulting constrainted optimization problem can be further expressed in the equivalent form as follows,

$$\begin{aligned} &\max \quad T(p_i,\alpha,\tau) = B(\tau) - A(\tau)\sum_{i=1}^{M} {p_i}^2 + \alpha\left(1-\sum_{i=1}^{M} p_i\right), \\ &\text{s.t.} \quad 0 \le p_i \le 1, \end{aligned} \tag{34}$$

where α is a Lagrange multiplier [23], corresponding to the constraint $\sum_{i=1}^{M} p_i = 1$ in (32), and

$$\begin{aligned} B(\tau) &= LN\frac{\tau(1-\tau)^{N-1} + (N-1)\tau^2(1-\tau)^{N-2}}{\sigma + T_s[1-(1-\tau)^N]}, \\ A(\tau) &= \frac{LN(N-1)\tau^2(1-\tau)^{N-2}}{\sigma + T_s[1-(1-\tau)^N]}. \end{aligned} \tag{35}$$

Note that the attempt probability τ in (33) is in fact a function of p_i through the fixed point equation defined earlier in (29). Due to the coupling between τ and p_i, finding the optimal solution by directly solving (32) would be difficult. In the following, we propose a heuristic algorithm to search for an optimal solution that fulfills the constraints in (32), and at the same time satisfies the fixed point equations. In particular, τ can be numerically computed using (15), (18) and (29) while in each of the iterations of the fixed point we also optimize the objective in (34) using the (fixed) τ value from the previous iteration. Denote the fixed point equations (15), (18) and (29) by a function $f()$ where we write

$$\tau = f(\tau, p_i).$$

The details of the proposed algorithm are described below.

Algorithm 1 An optimization framework: Combined fixed point and throughput optimization

Require: $\lambda, W, \sigma, T_{data}, T_{SIFS}, T_{ACK}, T_{DIFS}$ and a threshold $\delta > 0$
1: $n = 0,\ \tau = \tau(n)$ // Initialization
2: **repeat**
3: Find : $p_i^* \triangleq \underset{p_i}{\operatorname{argmax}}\ T(p_i, \alpha, \tau(n))$
4: Set n = n+1
5: Set $\tau(n) = f(\tau(n-1),\ p_i^*)$
6: **until** $|\tau(n) - \tau(n-1)| \le \delta$
7: Set $\tau = \tau(n)$

In this particular case, the searching for an optimal solution (line 3 in the Algorithm 1) is fairly simple and can be solved explicitly. It is because for a given fixed $\tau(n)$ value in the n^{th} iteration, the optimal p_i and α (denoted as p_i^* and α^*) can be obtained by differentiating (34) with respect to p_i and α and then setting the derivative to 0. This gives $2Ap_i^* + \alpha^* = 0$ and $\alpha^* = -\frac{2A}{M}$. Therefore, we have

$$p_i^* = \frac{1}{M}. \tag{36}$$

Note that the p_i^* solution turns out to be independent of τ and thus we only need to solve the optimization in line 3 in the Algorithm 1 once and then apply to all the iterations until the value τ converges. In summary, when there is no power constraint, uniformly choosing the discrete power achieves the optimal system throughput.

B. With Power Constraint

When the average consumed power cannot exceed a given limit E_{av}, (32) is modified as follows,

$$\begin{aligned} \max \quad & LN\frac{\tau(1-\tau)^{N-1}+(N-1)\tau^2(1-\tau)^{N-2}(1-\sum_{i=1}^{M}p_i^2)}{\sigma+T_s[1-(1-\tau)^N]} \\ \text{s.t.} \quad & \sum_{i=1}^{M}p_i=1, \\ & \sum_{i=1}^{M}p_i\tau E_i\le E_{av}, \\ & 0\le p_i\le 1, i=0,\dots M. \end{aligned} \tag{37}$$

Again, the proposed heuristic Algorithm 1 can be used to determine the optimal solution p_i^* and the corresponding τ that satisfy the fixed point equations (15), (18) and (29). In particular, for a given fixed $\tau(n)$ value in the n^{th} iteration of the fixed point, the following convex optimization problem (38) should be solved in line 3 of the Algorithm 1.

$$\begin{aligned} \text{minimize} \quad & \sum_{i=1}^{M}p_i^2 \\ \text{subject to} \quad & \sum_{i=1}^{M}p_i=1, \\ & \sum_{i=1}^{M}p_i\tau E_i\le E_{av} \\ & 0\le p_i\le 1, \quad i=1,\dots M. \end{aligned} \tag{38}$$

However, in this scenario (i.e. with power constraint) the solution p_i^* is generally dependent on τ values and thus the optimization solution is sought in each and every iteration (line 3 of the Algorithm 1) until the algorithm converges.

C. Fading Channels

In order to optimize the system throughput for the case of fading channels, we need to find the optimal $p_i(g)$ for each channel gain g. However, in general, g is continuously distributed, this makes finding the exact optimal solution impractical, if not impossible. To simplify the problem, we approximate the continuous distribution by a discrete distribution as follows. We divide the range of g, $[0,\infty)$, into H intervals according to $H+1$ thresholds $\{g^h|h=0,\dots,H\}$, and assume uniform distribution within each interval. That is

$$p_i(g)=p_i^h, g\in[g^{h-1},g^h), h=1,2,\dots,H \quad i=1,2,\dots M. \tag{39}$$

Clearly, $\sum_{i=1}^{M}p_i^h=1$, $\forall h$. Then,

$$p_i=\sum_{h=1}^{H}p_i^h q^h, \tag{40}$$

where $q^h=\int_{g\in[g^{h-1},g^h)}\Psi(g)dg$.

When the received power is E_i, and the channel gain is $g\in[g^{h-1},g^h)$, the corresponding transmitted power is E_i/g with probability density $p_i^h\tau\Psi(g)$. The average transmitted power is thus given by

$$\sum_{h=1}^{H}\sum_{i=1}^{M}\int_{g\in[g^{h-1},g^h)}(E_i/g)p_i^h\tau\Psi(g)dg=\sum_{h=1}^{H}\sum_{i=1}^{M}p_i^h\tau E_i/\overline{g}^h, \tag{41}$$

where $1/\overline{g}^h=\int_{g\in[g^{h-1},g^h)}\frac{1}{g}\Psi(g)dg$.

Thus, the throughput optimization problem can be formulated as

$$\begin{aligned} \max \quad & T=LN\frac{\tau(1-\tau)^{N-1}+(N-1)\tau^2(1-\tau)^{N-2}(1-\sum_{i=1}^{M}p_i^2)}{\sigma+T_s[1-(1-\tau)^N]} \\ \text{s.t.} \quad & 0\le p_i^h\le 1, i=1,\dots M, h=1,\dots H \\ & p_i=\sum_{h=1}^{H}p_i^h q^h, i=1,\dots M \\ & \sum_{i=1}^{M}p_i^h\tau\le 1, h=1,\dots,H \\ & \sum_{i=1}^{M}\sum_{h=1}^{H}p_i^h q^h=1 \\ & \sum_{i=1}^{M}\sum_{h=1}^{H}p_i^h\tau\frac{E_i}{\overline{g}^h}\le E_{av}. \end{aligned} \tag{42}$$

Using the same approach as before, the optimal throughput and the corresponding τ and p_i^h can be found by solving the following convex optimization problem (corresponding to line 3 of Algorithm 1) and iterating through the different τ values of the loop in the Algorithm 1.

$$\begin{aligned} \text{minimize} \quad & \sum_{i=1}^{M}p_i^2 \\ \text{subject to} \quad & 0\le p_i^h\le 1, i=1,\dots M, h=1,\dots H \\ & p_i=\sum_{h=1}^{H}p_i^h q^h, i=1,\dots M \\ & \sum_{i=1}^{M}p_i^h\tau\le 1, h=1,\dots,H \\ & \sum_{i=1}^{M}\sum_{h=1}^{H}p_i^h q^h=1 \\ & \sum_{i=1}^{M}\sum_{h=1}^{H}p_i^h\tau\frac{E_i}{\overline{g}^h}\le E_{av}. \end{aligned} \tag{43}$$

D. Numerical Results

Using the above approaches, we evaluate the p_i^*, and optimal normalized system throughput (denoted as T^*) for various E_{av} with $M=3,5$. The network has the following parameters: $N=10$, $\lambda=200$, at the MAC layer (DCF scheme) $W=32$, $m=5$, $K=7$, and at the physical layer (SPR scheme) $R=1$, $N_0=1$. We first consider the case of AWGN channel. Table II tabulates p_i^* and T^* for various E_{av} and M. It can be seen that for a given M, when E_{av} is small, a node is restricted to choose low power levels in order to satisfy the power constraint. As E_{av} is increased, more higher power levels can be chosen with some small probabilities. Eventually, when E_{av} is large enough, practically all power levels can be chosen and p_i^* converges to uniform distribution, which corresponds to the case of no power constraint as shown in Section V-A. For a smaller M, p_i^* converges to uniform distribution at a lower E_{av} because E_M is smaller.

TABLE II: Optimal p_i under AWGN channels.

E_{av}	$M=3$	$M=5$
0.08	$p_i^*=(0.5091, 0.3333, 0.1576)$ $T^*=0.3802$	$p_i^*=(0.5091, 0.3333, 0.1576, 0.0, 0.0)$, $T^*=0.3802$
0.1	$p_i^*=(0.3353, 0.3333, 0.3313)$ $T^*=0.389$	$p_i^*=(0.4047, 0.3007, 0.1990, 0.0956, 0)$, $T^*=0.3935$
0.12	$p_i^*=(0.3343, 0.3323, 0.3335)$ $T^*=0.389$	$p_i^*=(0.3346, 0.2667, 0.1999, 0.1331, 0.0657)$, $T^*=0.4021$
0.14	$p_i^*=(0.333, 0.333, 0.333)$ $T^*=0.389$	$p_i^*=(0.2640, 0.2320, 0.2000, 0.1680, 0.1360)$ $T^*=0.4075$
0.16		$p_i^*=(0.2057, 0.2029, 0.2000, 0.1971, 0.1943)$, $T^*=0.409$
0.18		$p_i^*=(0.1974, 0.2000, 0.2004, 0.2009, 0.2013)$, $T^*=0.4091$
0.20		$p_i^*=(0.2, 0.2, 0.2, 0.2, 0.2)$ $T^*=0.4091$

For the optimal throughput, it initially increases with E_{av}. This is because when E_{av} increases, the optimal solution contains more non-zero p_i^*, which means that nodes have more power levels to choose. As a result, the probability of collision due to simultaneous transmission with the same power level decreases and the optimal throughput increases. Eventually, when E_{av} is sufficiently large that p_i^* becomes uniformly distributed, the collision probability becomes minimal and hence the optimal throughput becomes maximum. Further increase of E_{av} will not increase the optimal throughput anymore.

Next, we evaluate the optimal throughput in fading channels for various E_{av} with $M=3,5$. A Rayleigh fading channel with averaged power gain 1 for all users is assumed. We divide the whole range of g, i.e., $[0,\infty)$, into H intervals with $H=20$. Referring to Table III, surprisingly, a higher throughout than that of AWGN channels is attained. It can be seen that the maximum attainable throughput over an AWGN channel can be already achieved with a non-uniform distribution of p_i^* and small value of E_{av}. This is because in this setting of fading channels, the probability that g is less than one is large, thus less transmission power is consumed to achieve E_i at the receiver. Therefore, for a given E_{av}, more power levels are realizable at the receiver. We learned from the earlier results that when more power levels are available, the throughput performance is improved.

VI. Throughput Optimization in Ad Hoc Mode

In Section V, we have derived the expressions of p_i to maximize the system throughput for the infrastructure mode. In this mode the access point would determine the optimal

TABLE III: Optimal p_i under fading channels.

E_{av}	$M=3$	$M=5$
0.08	$p_i^*=(0.3333, 0.3333, 0.3333)$ $T^*=0.3890$	$p_i^*=(0.2008, 0.2214, 0.205, 0.192, 0.1809)$, $T^*=0.4089$
0.1		$p_i^*=(0.2044, 0.219, 0.2041, 0.1917, 0.1808)$, $T^*=0.4089$

probabilities for a given discrete power profile and then broadcast to all nodes for their reference to choose the power levels. However, in ad-hoc mode there is no central controller, such as the access point, to carry out the coordination in the network. Instead, each node can only determine its PMF of power levels independently to optimize its own throughput. Such a problem is best modeled as a non-cooperative mixed strategy game where users selfishly act on their best interest. As in Section V, below we consider the cases with and without power constraint, respectively.

A. With Power Constraint

Recall that whether a node will transmit a packet on the wireless channel is determined by its backoff process governed by the DCF scheme. Thus, from the perspective of node i, whenever it attempts to send a packet, it is playing a game with possibly $k=0,1,\ldots,N-1$ other nodes, whose DCF might also decide to transmit in the same slot. Let us denote a game with a total of j $(j>1)$ players as G_j. Note that the condition $j>1$ stems from the fact that a game requires at least 2 players. The case of $j=1$ is essentially a traditional operation of WLANs without any multiple packet reception capability.

At a first glance, the game model of our problem involves $G_2, \ldots G_N$. However, under the SPR scheme, collision involves three or more simultaneous transmissions can not be resolved and therefore no node can gain any throughput. For this reason, in G_j $(\forall j>2)$ games, no matter what PMF each node chooses, no throughput gain ever eventuates. In other words, the user's strategies do not have any impact on the utility and thus $G_j, j=3,4,\ldots,N$ are not valid games.

It remains to study the G_2 game. In this game, the two users can choose between several discrete power levels $E_1,..,E_M$ where $E_{i+1}>E_i, i=1,..,M-1$ when deciding to transmit a packet on the wireless channel in any given time slot.

To simplify the explanation, we first consider a pure strategy game in which each player chooses a power level to transmit a packet when its DCF protocol allows it to do so. Then, G_2 can be formally expressed as a 3-tuple $(\mathcal{N}, S, U_i(.))$, where $\mathcal{N}=\{1,2\}$ is the player set, $S=\mathcal{E}\equiv\{E_1,E_2,\ldots,E_M\}$ is the strategy set of all players, and $U_i(.)$ is the utility function of player $i, i=1,2$, that equals to zero when the obtained throughput is zero.

In the presence of the power constraint, it means that each node always tries to achieve a certain throughput with the least possible power. Under SPR, if the two players choose the same strategy, collision cannot be resolved, and both of their utilities are zero. On the other hand, if their strategies are different, both get one packet through, and we say that

TABLE IV: Payoffs of the pure strategy game

	E_1	E_2	$\dots$	E_M
E_1	(0,0)	$(1{-}\alpha\frac{E_1}{E_M}, 1{-}\alpha\frac{E_2}{E_M})$	$\dots$	$(1{-}\alpha\frac{E_1}{E_M}, 1{-}\alpha)$
E_2	$(1{-}\alpha\frac{E_2}{E_M}, 1{-}\alpha\frac{E_1}{E_M})$	(0,0)	$\dots$	$(1{-}\alpha\frac{E_2}{E_M}, 1{-}\alpha)$
E_3	$(1{-}\alpha\frac{E_3}{E_M}, 1{-}\alpha\frac{E_1}{E_M})$	$(1{-}\alpha\frac{E_3}{E_M}, 1{-}\alpha\frac{E_2}{E_M})$	$\dots$	$(1{-}\alpha\frac{E_3}{E_M}, 1{-}\alpha)$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
E_M	$(1{-}\alpha, 1{-}\alpha\frac{E_1}{E_M})$	$(1{-}\alpha, 1{-}\alpha\frac{E_2}{E_M})$	$\dots$	(0,0)

each player get one unit of utility. However, their utility should be discounted by the amount of consumed power. Hence, we design the utility functions of player 1 and player 2, as follows. Let $s_i \in S$ be the strategy of player i, their respective utility can be written as

$$U_1(s_1, s_2) = \begin{cases} 0 & s_1 = s_2, \\ 1 - \alpha(s_1/E_M) & s_1 \neq s_2, \end{cases} \tag{44}$$

and

$$U_2(s_1, s_2) = \begin{cases} 0 & s_1 = s_2, \\ 1 - \alpha(s_2/E_M) & s_1 \neq s_2, \end{cases} \tag{45}$$

where $\alpha < 1$ is a constant factor represents the relative importance between throughput and power usage.

This game can be represented by Table IV. The first column and the first row of Table IV denote the possible strategies of player 1 and player 2, respectively. Each entry in Table IV denotes the utility functions of them, i.e., (U_1, U_2).

By inspection, one can find that the two strategy profiles, (E_1, E_2) and (E_2, E_1), are Nash equilibria as neither player can get a higher utility by deviating unilaterally from the profiles. Moreover, these two profiles are Pareto optimal because, for each profile, a player cannot increase his payoff without making the payoff of the other player worse. Note that neither of the players will consider using a power level that is higher than E_2 because it will further decreases the utility value.

From above, the rational choice of each player is either E_1 or E_2. So, the above game can be reduced to a mixed strategy game with two possible strategies, which is represented by Table V.

TABLE V: Payoffs of the mixed strategy game

	E_1	E_2
E_1	(0,0)	$(1-\alpha\frac{E_1}{E_M}, 1-\alpha\frac{E_2}{E_M})$
E_2	$(1-\alpha\frac{E_2}{E_M}, 1-\alpha\frac{E_1}{E_M})$	(0,0)

Let us denote the probability of choosing E_1 and E_2 by p_1 and p_2, respectively. From the perspective of player 1, his expected payoff (F_1) when choosing E_1 is given by $p_2(1-\alpha(E_1/E_M))$. Similarly, his expected payoff (F_2) when choosing E_2 is $p_1(1-\alpha(E_2/E_M))$. By the equality of payoffs lemma [24], set $F_1 = F_2$, we have

$$p_2(1-\alpha(E_1/E_M)) = p_1(1-\alpha(E_2/E_M)). \tag{46}$$

TABLE VI: Payoffs of mixed strategy game without power constraint

	$E_1(p_1)$	$E_2(p_2)$	$E_3(p_3)$	$\dots$	$E_M(p_M)$
$E_1(p_1)$	(0,0)	(1,1)	(1,1)	$\dots$	(1,1)
$E_2(p_2)$	(1,1)	(0,0)	(1,1)	$\dots$	(1,1)
$E_3(p_3)$	(1,1)	(1,1)	(0,0)	$\dots$	(1,1)
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$E_M(p_M)$	(1,1)	(1,1)	(1,1)	$\dots$	(0,0)

With the condition $p_1 + p_2 = 1$, p_1 and p_2 can be solved for as follows,

$$p_i = \frac{E_M - \alpha E_i}{2E_M - \alpha(E_1 + E_2)}, \quad \text{for } i = 1, 2. \tag{47}$$

Since this is a symmetric game, the other player will also adopt this probability distribution to choose the power levels. In other word, each node chooses the power levels with the same probability distribution and achieves the same throughput. Hence, the solution of the mixed strategy game results in a fair distribution of the system throughput.

The power distribution in (47) represents the strategy that a node will follow in a two-player game when selecting its power levels to transmit a packet *provided* that it knows that there will be a contending node in the same time slot. This strategy results in Nash equilibria as discussed earlier. However, in practice, a node would not know whether there is another node transmitting in the same time slot. Yet still, using the strategy in (47) gives a node a chance to recover its packet should collision occur. The average consumed power per node in this case is $\tau(p_1E_1 + p_2E_2)$ which is slightly higher than τE_1, the power consumed in the traditional WLANs but without multiple packet reception. This small increase in average power is the cost to achieve the significant throughput improvement using SPR as shown in Sec IV-B.

B. Without Power Constraint

Similar to the case with power constraint, we just need to focus on G_2 game. When there is no power constraint, the utility function given by (44) and (45) can be simplified by removing the dependence on the power level. When a node transmits one packet successfully, it gets one unit of utility. Then, we have a 2-player game which is formulated as Table VI.

Each player chooses power level E_i with probability p_i. Therefore, for player 1, the expected payoffs are obtained as follow,

$$\begin{aligned} F_1 &= p_2 + p_3 + \ldots + p_M = 1 - p_1, \\ F_2 &= p_1 + p_3 + \ldots + p_M = 1 - p_2, \\ &\vdots \\ F_M &= p_1 + p_2 + \ldots + p_{M-1} = 1 - p_M. \end{aligned} \tag{48}$$

Similarly, according to the equality of payoffs lemma, set $F_1 = F_2 = \ldots = F_M$ which gives,

$$1 - p_1 = 1 - p_2 = \ldots = 1 - p_M. \tag{49}$$

And with the condition of $\sum_{i=1}^{M} p_i = 1$, we obtain

$$p_i = \frac{1}{M}, \quad i = 1, \ldots, M. \tag{50}$$

The other player will also adopt this probability distribution to choose power levels since this is a symmetric game. As we can see, when there is no power constraint, uniform power distribution leads to the optimal throughput. Interestingly, when there is no power constraint, uniform distribution of discrete power levels leads to optimal throughput for both infrastructure and ad-hoc modes.

C. Numerical Results

Let us consider a WLAN network under ad-hoc mode with the following parameters: $M = 5$, $N = 10$, $\lambda = 200$, and $R = 1$, $N_0 = 1$ which gives the strategy set $\mathcal{E} = \{1, 2, 3, 4, 5\}$. The parameter α is set to be 0.2, 0.5, 0.9 and 1, the corresponding probabilities p_1 and p_2 are given by Table VII. Note that $\alpha = 1$ represents the case where throughput and power are equally important in the utility function. Based on each pair of p_1 and p_2, we calculate the corresponding system throughput using the model from Section IV and validate by simulation. These results are reported in Table VII. It can be seen that the simulation and numerical results match well.

TABLE VII: Different probabilities and system throughputs for various α

α	p_1	p_2	Throughput (analysis)	Throughput (simulation)
0.2	0.5106	0.4894	0.3661	0.366939
0.5	0.5294	0.4706	0.3659	0.366574
0.9	0.5616	0.4384	0.3651	0.365589
1	0.5714	0.4286	0.3648	0.364956

From the probabilities given in Table VII, we can calculate the average consumed power in ad-hoc mode,

$$E_{av} = \sum_{i=1}^{M} \tau p_i E_i. \tag{51}$$

Then, using this as the average power constraint in the optimization formulation in (37), we can obtain the corresponding optimal throughput, which is denoted as T_O, as well as the optimal PMF for the infrastructure mode. Let us denote the optimal throughput under the ad-hoc mode by T_G. Table VIII compares T_G and T_O for different number of nodes N.

From Table VIII, we can see that, for different values of α, the optimal throughput obtained in the ad-hoc mode is smaller than, but very close to, that obtained in the infrastructure mode. The reason is that, given the same average power consumption, the transmission power levels that will be chosen are E_1 and E_2 in ad-hoc mode, while they are E_1, E_2 and E_3 in the infrastructure mode (since $p_4 = p_5 = 0$), as shown in Table VIII. For this reason the probability of two nodes choosing the same transmission power level in the ad-hoc mode is slightly larger than that in the infrastructure mode. This results in a smaller throughput in the ad-hoc mode. Nevertheless, the difference denoted by $T_O - T_G$ and commonly referred to as the *price of anarchy* is very small.

As the number of power levels M increases, similar results are observed with the price of anarchy remaining as small as that of the case for $M = 5$. It is because even when M is increased, each node still only chooses among the lowest two or three levels of power in the ad-hoc and infrastructure modes, respectively. As a result the collision probability and hence the throughput in ad-hoc mode is not much worse off than that in infrastructure mode.

VII. Conclusion

In this paper, we have developed an analytical model to evaluate the throughput performance of IEEE 802.11 networks with the multiple-packet reception capability based on successive interference cancellation and randomized transmission power. Compared to the original 802.11 networks, the throughput is significantly improved. Moreover, we have provided the optimal probability mass function of the power levels in order to maximize the network throughput in both infrastructure and ad-hoc modes. In the infrastructure mode, the problem was formulated as an optimization problem where an efficient fixed-point algorithm to obtain the optimal probability mass function was proposed. In the ad hoc mode, the problem was formulated as a mixed strategy game, and its Nash equilibrium was found and showed to be Pareto optimal and fair. Even though there is no central controller in the ad-hoc mode, its optimal throughput is very close to that of infrastructure mode, which makes this multiple-packet reception scheme suitable for both operating modes of the 802.11 networks.

A possible direction of future work is to investigate the performance improvement when SIC is replaced by spatially-coupled low-density parity-check codes [25], which has been shown recently to suppress interference more efficiently.

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TABLE VIII: Comparing optimal throughput of ad-hoc mode and infrastructure mode for for M=5.

α	E_{av}	(p_1, p_2) (ad-hoc mode)	(p_1, p_2, p_3) (infrastructure mode)	$N = 5$			$N = 10$			$N = 20$		
				T_G	T_O	$T_O - T_G$	T_G	T_O	$T_O - T_G$	T_G	T_O	$T_O - T_G$
0.2	0.06926	$(0.5106, 0.4894)$	$(0.5886, 0.3333, 0.078)$	0.3628	0.3657	0.0029	0.3661	0.3709	0.0048	0.357	0.3631	0.0061
0.5	0.06839	$(0.5294, 0.4706)$	$(0.598, 0.3333, 0.0686)$	0.3627	0.3649	0.0022	0.3659	0.3696	0.0037	0.3567	0.3614	0.0044
0.9	0.06689	$(0.5616, 0.4384)$	$(0.6141, 0.3333, 0.0525)$	0.3622	0.3635	0.0013	0.3651	0.3673	0.0022	0.3558	0.3585	0.0027
1	0.06643	$(0.5714, 0.4286)$	$(0.619, 0.3333, 0.0476)$	0.3620	0.3631	0.0011	0.3648	0.3665	0.0017	0.3554	0.3576	0.0022

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Mingrui Zou received her B.S. degree in Electronics and Information Engineering from Sichuan University, Chengdu, China, and her M.S. degree in Information Technology & Telecommunication from Inha University, Incheon, Korea, in 2007 and 2009, respectively. In 2013, she received her Ph.D. degree in Electronic Engineering at City University of Hong Kong. Since then, she works as a research assistant at China Academy of Engineering Physics in Mianyang, China. Currently, her research interest is focused on Terahertz Wireless Communication related issues.

Sammy Chan (S'87-M'89) received his B.E. and M.Eng.Sc. degrees in electrical engineering from the University of Melbourne, Australia, in 1988 and 1990, respectively, and a Ph.D. degree in communication engineering from the Royal Melbourne Institute of Technology, Australia, in 1995. From 1989 to 1994, he was with Telecom Australia Research Laboratories, first as a research engineer, and between 1992 and 1994 as a senior research engineer and project leader. Since December 1994, he has been with the Department of Electronic Engineering, City University of Hong Kong, where he is currently an associate professor.

Hai L. Vu (S'97–M'98–SM'06) received the BSc/MSc, and PhD degrees in electrical engineering from the Technical University of Budapest, Hungary, in 1994 and 1999, respectively. From 1994 to 2000, he was a research engineer with Siemens AG, Hungary. Between 2000 and 2005, he was with the Department of Electrical and Electronic Engineering, the University of Melbourne, Australia. In 2005, he joined the Swinburne University of Technology, where he currently is the Head of the Intelligent Transport Systems Research Lab. Since 2012, he is a Professor in the Faculty of Science, Engineering & Technology, Swinburne and is an Australian Research Council (ARC) Future Fellow. He has authored or coauthored more than 150 scientific journals and conference papers. His research interests include performance analysis and design of wireless data networks, and stochastic optimization with applications to intelligent transport systems. He is a senior member of the IEEE since 2006.

Li Ping (S87-M91-SM06-F10) received his Ph.D. degree at Glasgow University in 1990. He lectured at Department of Electrical and Electronic Engineering, the University of Melbourne, from 1990 to 1992, and worked as a research staff at Telecom Australia Research Laboratories from 1993 to 1995. Since January 1996, he has been with the Department of Electronic Engineering, City University of Hong Kong, where he is now a chair professor of information engineering. Prof. Li Ping received the IEE J J Thomson premium in 1993, the Croucher Foundation Award in 2005 and a British Royal Academy of Engineering Distinguished Visiting Fellowship in 2010. He served as a member of the Board of Governors for IEEE Information Theory Society from 2010 to 2012 and is a fellow of IEEE.