Performance Enhancement of Adaptive Orthogonal Modulation in Wireless CDMA Systems

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Abstract

Recent research in wireless CDMA systems has shown that adaptive rate/power control can considerably increase network throughput relative to systems that use only power or rate control. In this paper, we consider joint power/rate optimization in the context of orthogonal modulation (OM) and investigate the additional performance gains achieved through adaptation of the *OM order*. We show that such adaptation can significantly increase network throughput while simultaneously reducing the per-bit energy consumption relative to fixed-order modulation systems. The optimization is carried out under two different objective functions: minimizing the maximum service time and maximizing the sum of user rates. For the first objective function, we prove that the optimization problem can be formulated as a generalized geometric program (GGP). We then show how this GGP can be transformed into a nonlinear convex program, which can be solved optimally and efficiently. For the second objective function, we obtain a lower bound on the performance gain of adaptive OM (AOM) over fixed-modulation systems. Numerical results indicate that relative to an optimal joint rate/power control fixed-order modulation scheme, the proposed AOM scheme achieves significant throughput and energy gains.

I. Introduction

Efficient utilization of the limited wireless spectrum while satisfying applications' quality of service (QoS) requirements is an essential design goal of fourth-generation (4G) wireless networks and a key to their successful deployment [46]. Despite their appealing simplicity, resource allocation policies in currently deployed wireless networks, such as the IEEE 802.11, are inefficient, perform poorly under moderate loads [10], and are unable to match the growing demand for high data rates.

The need for spectrally efficient systems has motivated the development of adaptive transmission techniques, several of which are in the process of being standardized. These techniques adapt users' parameters according to the time-varying channel conditions, interference levels, rate requirements, bit error rate (BER) needs, and energy constraints [29].

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In *narrow-band* (i.e., non-spread spectrum) systems, adaptation includes varying the transmission power [16], modulation order [14], symbol rate [9], coding rate [41], or any combination of these parameters [3], [13], [15], [28]. In particular, it is well known that adaptive modulation is a promising technique for increasing the user data rate in narrow-band systems. This was demonstrated in [14] for the single-user case, where it was shown that adaptive modulation can provide up to 10 dB gain over a fixed-rate system that uses only power control. In [33], the authors studied the multiuser case and showed that even without power control, adaptive modulation has a significant throughput advantage over fixed-rate power control schemes. Much of the work on adaptive modulation in narrow-band systems (e.g., [4], [14], [23], [24], [43]) has been motivated by recent advances in designing low-complexity adaptive modulation circuitry and channel estimation techniques [14].

In the context of (wide-band) direct-sequence code division multiple access (CDMA) networks, power control has traditionally been the single most important adaptation parameter [12], and has been thoroughly studied (see [37] and the references therein). Recent efforts on adaptation in CDMA networks have also focused on adapting the transmission rate using multiple codes [18], [36], parallel combinatory spread spectrum [48], multiple chip-rate [44], adaptive modulation and coding (AMC) [1], [6], [17], and "classical" variable processing gain (VPG) techniques [10], [11], [19], [22], [25], [27], [30], [35], [42], [45] in which both the transmission power and data rate are adapted, but the modulation and coding are kept fixed.

For CDMA systems that require coherent reception, a pilot signal must usually be transmitted for each user. This is the case, for example, in WCDMA systems [1], where a high-rate coherent two-dimensional modulation[1] such as 16QAM [1], [17] is used. Alternatively, to reduce the implementation complexity associated with coherent reception (e.g., recovering the pilot signals from users) and to potentially improve energy efficiency (a pilot signal consumes a considerable amount of the mobile user's energy), noncoherent reception can be used [21]. M-ary orthogonal modulation (OM) is a spectrally-efficient modulation technique that is well suited for this application [12]. Although differential phase shift keying (DPSK) can also be used for noncoherent reception, it has been shown that OM outperforms DPSK for $M > 8$ in additive white Gaussian noise (AWGN) and in Rayleigh fading channels [32]. OM has been used successfully in the uplink of IS-95 and is also part of the radio configurations of the cdma2000 standard [18].

This paper focuses on CDMA systems for which coherent reception is not possible and where OM is used (e.g., uplink IS-95). For such systems, classical (i.e., fixed OM order) VPG has been the focus of research because of its performance benefits, flexibility, and practicality (e.g., low peak-to-mean envelope power, fixed chip rate, etc. [19]). The extensive work on VPG has clearly quantified the performance[2] advantages of combined rate/power control over power control alone (e.g., see [35], [19]). However, to the best of our knowledge, adapting the modulation order for variable-rate OM-based systems remains an unexplored area of research, and one for which joint rate/power control has not yet been investigated. Our first contribution (Section II) is to show that when OM is used, the performance of variable-rate CDMA

[1]By two-dimensional modulation, we mean modulation schemes for which the modulation symbol can be represented by a 2-dimensional vector, i.e., by a point in the 2-dimensional signal space (or constellation).

[2]Throughout the paper, the term "performance" is used to refer to network throughput and/or per-bit energy consumption.

networks can be improved by using higher OM orders at lower data rates. We then use these results to show that, in the single link case, variable-rate systems with adaptive orthogonal modulation (AOM) significantly outperforms VPG systems with a fixed OM order[3]. Thus, similar to adaptive modulation in narrow-band systems, AOM in CDMA systems is shown to be a promising technique for increasing the user data rate. Note that the processing gain and transmission power are varied in both AOM and VPG. However, in AOM the OM order is also varied depending on the data rate, whereas VPG uses the *same* OM order for all data rates.

The main goal of our study is to investigate the theoretical performance limits of *joint* rate/power control for AOM-based CDMA networks and to gain insights into the technique itself. We consider both point-to-point (PTP) as well as multipoint-to-point (MultiPTP) networks (see Figure 1). PTP networks is the more general communication paradigm. It can represent a completely distributed mobile ad hoc network, or a microcellular network in which mobile-base station pairs compete for the same frequency spectrum. In MultiPTP networks, multiple nodes transmit to one node, as in the case of a cluster-based ad hoc or sensor network [31] or in the case of the uplink of a single cell in a CDMA-based cellular network (e.g., IS-95 [32]). With very few exceptions, previous work has mainly considered MultiPTP networks.

(a) PTP Networks. (b) MultiPTP Networks.

Fig. 1. Network topologies considered in the paper.

To jointly optimize the powers and rates, we consider two *throughput-related* objective functions: (1) minimizing the maximum service time, and (2) maximizing the sum of users' transmission rates. Both functions are optimized subject to constraints on the maximum transmission power, on the minimum and maximum transmission rates, and on the BER. The first function is novel in our context and has not received much attention; previous research has primarily focused on the second objective function. However, as we argue in Section III, there are important *practical* advantages of the first objective function.

We obtain the optimum solution to the problem of minimizing the maximum service time in both PTP and MultiPTP networks by formulating the problem as a generalized geometric program (GGP) [8]. We then transform this GGP into a geometric program (GP), which itself can be transformed into a nonlinear convex program. The advantage of these transformations is that a convex program has a global optimum that can be found very efficiently [8]. Furthermore, in the case of MultiPTP networks, we derive a simple expression for computing the optimal powers and rates that minimize the maximum service time. Our solutions are computationally efficient. They can also be used to determine the feasibility of

[3]For brevity, we use the acronym AOM to refer to a variable-rate system with adaptive OM, while the acronym VPG refers to a variable-rate system with a fixed OM order.

a set of rate and BER requirements under certain constraints, thus, allowing for the use of admission control policies.

Although the second objective function (i.e., maximizing the sum of rates) has the advantage of being in the exact form of throughput, it has the limitation of having several local maxima. As a result, there are no computationally efficient algorithms to solve this problem[4]. Hence, for PTP networks, although we do not know the optimal rate/power solution for VPG and AOM, we provide some numerical results that demonstrate the performance advantages of AOM over VPG. For MultiPTP networks, we start from theorems proved in [19], and we analytically derive a simple procedure for maximizing the sum of rates for VPG systems. Then, we show how this solution, which is optimal in VPG systems, can be used *heuristically* in AOM MultiPTP networks. Using these results, we derive a lower bound on the achievable gain of AOM over VPG schemes. As shown in Section IV, this gain is substantial.

Note that our goal in this paper is *not* to promote OM as a modulation scheme, but rather to advocate *adapting* the order of OM for CDMA systems that already use OM (e.g., the uplink of IS-95). The rest of the paper is organized as follows. In the next section, we take a system-level approach to the analysis of AOM in CDMA multimedia networks and show its performance advantages over VPG. In section III, we present the objective functions, formulate the optimization problems, and present their solutions. The performance of AOM is presented and contrasted with VPG in Section IV. Finally, our main conclusions and several open issues are drawn in Section V.

II. Orthogonal Modulation in CDMA Networks

A. Motivation for Higher Orthogonal Modulation Orders

The main goal of this section is to show that for any data rate, increasing the OM order improves the performance of a CDMA system. The maximum OM order that can be used, however, is constrained by the chip rate. We first start with a system-level analysis of CDMA systems. The benefits of a higher OM order is then established using this analysis and through an analogy between OM and FEC. The message we will try to convey is that, in CDMA systems, it is always advantageous to use an FEC or an OM order that reduces the bit-energy-to-noise spectral density ratio (E_b/N_0) required for a given BER.

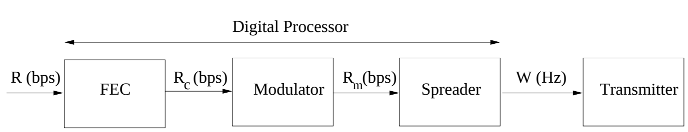


Fig. 2. Simplified block diagram of the transmitter circuit.

The transmitter circuit of the system under study is shown in Figure 2. It consists of (digital) FEC encoder, modulator, direct-sequence spreader, and (analog) amplifier and transmitter [12]. Consider packet reception for link i. Let I be the set of active links in the network, $P_t^{(i)}$ be the transmission power of link i, and h_{ji} be the channel gain between the

[4]This may be one reason why previous studies that pursued an algorithmic approach to this problem considered other objectives, such as minimizing the power or even *minimizing* the sum of rates [25].

receiver of link i and the transmitter of link j. Then the signal-to-noise (and interference) ratio at i is:

$$\text{SNR}^{(i)} = \frac{h_{ii}P_t^{(i)}}{\sum\limits_{j \in I-\{i\}} h_{ji}P_t^{(j)} + P_{\text{thermal}}} \tag{1}$$

where P_{thermal} is the thermal noise, which is modeled as a white Gaussian noise process. The interference from other users is also assumed to be Gaussian. This assumption has been shown to produce throughput results that are reasonably accurate [34]. For reliable communication, a more relevant metric than $\text{SNR}^{(i)}$ is the effective bit energy-to-noise spectral density ratio at the detector, denoted by $\mu^{(i)}$ and given by [12]:

$$\mu^{(i)} \stackrel{\text{def}}{=} \frac{E_b}{N_0} = \frac{W}{R^{(i)}} \frac{h_{ii}P_t^{(i)}}{\sum\limits_{j \in I-\{i\}} h_{ji}P_t^{(j)} + P_{\text{thermal}}} \tag{2}$$

where W is the Fourier bandwidth occupied by the signal (i.e., chip rate) and $R^{(i)}$ is the data rate of i's intended signal. Let μ_{req} be the required $\mu^{(i)}$ for a certain BER. Then, the maximum achievable data rate at i is:

$$R^{(i)} = W \frac{\text{SNR}^{(i)}}{\mu_{\text{req}}}. \tag{3}$$

Both (2) and (3), which hold for any CDMA system, do not explicitly indicate the effects of FEC and modulation on the achievable data rate. However, these effect appear indirectly through the value of μ_{req}. For example, the stronger the FEC code (i.e., the lower the code rate), the lesser is μ_{req} and the higher is the achievable data rate. This analysis is inline with the findings of Viterbi [40], in which he showed that the *jamming margin* is actually increased by coding; the idea is that with coding, μ_{req} is lower, and so more interference is allowed for the same rate (i.e., $\text{SNR}^{(i)}$ in (3) can be decreased). In other words, for CDMA systems it is always preferable to use schemes that enable operation at a lower μ_{req}.

In the case of M-ary OM, the modulator takes $k = \log_2 M$ FEC-coded bits and maps them into one of the M Walsh (or Hadamard) orthogonal sequences [32] of length M bits. So the resulting *modulated bit rate* R_m is equal to $R_c\, M/k$, where R_c is the coded bit rate (see Figure 2). At the receiver, the signal is first despread and then noncoherently detected, generating k soft output bits for each transmitted Walsh symbol, which are fed to the Viterbi decoder (see [39] for further details). A tight upper bound on the probability of bit error in OM is given by [32]:

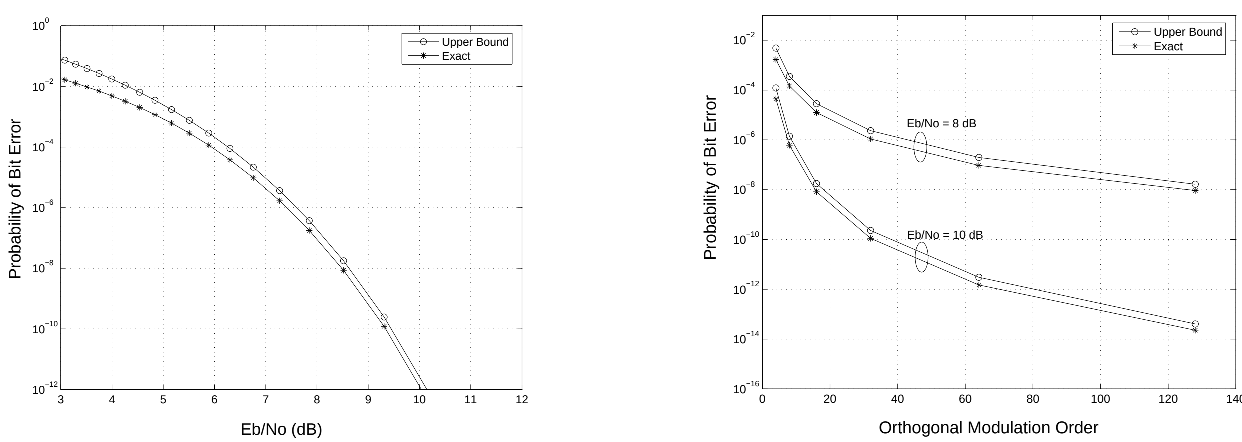
$$P_b < \frac{1}{2} e^{-k(\mu^{(i)} - 2\ln 2)/2}. \tag{4}$$

It is clear from (4) that the higher the value of k, the lower is the BER. *Therefore, the higher the OM order M, the better is the BER performance for the same E_b/N_0 value.* OM in this sense works as an FEC code; the higher the value of M, the lower is the modulation rate k/M, but the better is the BER performance. Note that the higher the OM order, the higher is R_m; however, this has no impact on the system bandwidth as long as $R_m \leq W$, since the signal is spread by a high-rate CDMA code.

B. Performance Advantages of Adaptive Orthogonal Modulation

In the previous section, we showed that increasing the OM order is beneficial for the performance of a CDMA network. However, the higher the user data rate R, the lower must be the maximum allowable M to ensure that $R_m \leq W$. Thus, in AOM, M must be adapted according to R. Our goal in this section is to quantify the performance gains of adapting M according to R. To do this, we derive the relationship between the user's SNR and the achievable data rate for AOM and for non-adaptive OM (i.e., VPG).

First, we claim that it is sufficiently accurate to use (2) and the upper bound in (4) to analyze OM in CDMA systems. To substantiate our claim, we compare the performance obtained from these two simple equations with the results reported in [26], which were obtained using rigorous analysis. We simulate the same setup of [26]: a MultiPTP network that uses 64-ary OM with equal received powers at the common receiver. The number of transmitters is varied to obtain different E_b/N_0. Part (a) of Figure 3 shows the probability of bit error versus E_b/N_0. The "exact" plot is the same one that was obtained in [26], while the upper-bound curve is the one obtained using (2) and (4). This figure demonstrates that the bound is sufficiently tight for all practical purposes. To verify the tightness of the bound for other values of M, we show in Part (b) of Figure 3 the probability of bit error versus M for $E_b/N_0 = 8$ dB and $E_b/N_0 = 10$ dB. As can be seen, the bound is tight, and hence will be used in our subsequent analysis.



(a) (b)

Fig. 3. Probability of bit error in an OM-based CDMA system.

Next, we use (2) and (4) to derive the relationship between the user's SNR and the achievable rate with and without adapting M. From this relationship, we demonstrate the performance advantages of AOM over VPG for the single-link case. Without loss of generality, we assume that the system under study does not use any FEC (i.e., $R_c = R$). VPG uses the *same* modulation order M for all data rates. This M is chosen such that for a given R, $R_m \leq Z \leq W$, where Z is a threshold that is often determined by regulatory laws. For example, the Federal Commission Commission (FCC) calls for at least a ratio of 10 (i.e., 10 dB) of spreading rate to modulation bit rate in the 2.4 GHz ISM band [5], so in this case

$Z = W/10$. Accordingly, the modulation order for VPG is decided based on W, Z, and the maximum desired data rate (R_{max}). If $Z = W$ and $R_{\text{max}} = W/2$, then the (fixed) modulation order $M = 2$. If the required BER is 10^{-6}, then for this VPG system, μ_{req} is about 14.8, and so using (3), the required SNR at R_{max} is 7.4. Note that whereas μ_{req} is fixed, the required SNR is a function of R.

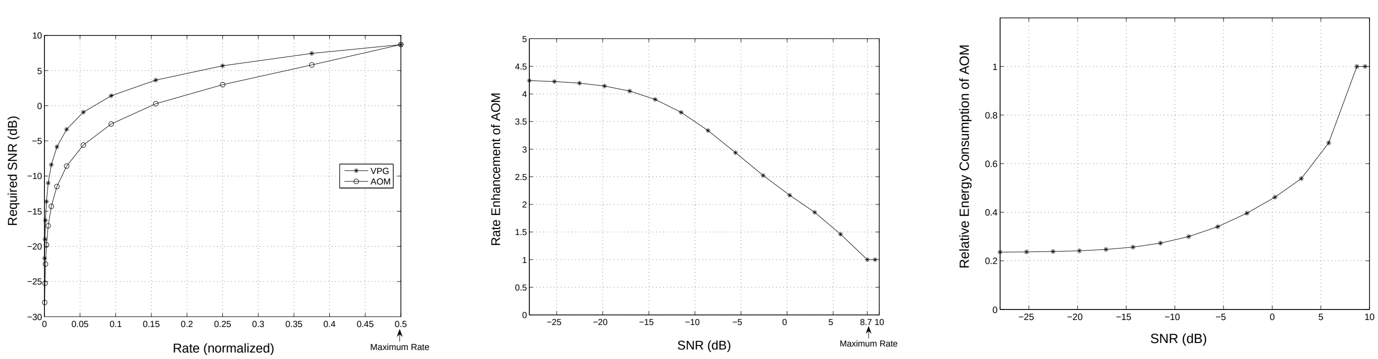
AOM, on the other hand, uses a variable M that depends on R. The higher the value of M, the smaller is the value of μ_{req}, but also the higher is R_m. For $Z = W$ and $R_{\text{max}} = W/2$, the value of M at R_{max} cannot exceed 2 (to ensure that $R_m \leq Z$), implying that there is no performance advantage of AOM over VPG at R_{max}. However, for $R < R_{\text{max}}$, AOM uses a higher value for M, enabling operation at a lower μ_{req}, or equivalently, resulting in a higher data rate (see (3)). For each data rate R, the corresponding value of M is the largest value such that R_m, which in the absence of FEC is equal to $R\,M/k$, does not exceed Z. Assuming M is continuous (more on this assumption shortly), R can be expressed as:

$$R = Z\,k\,2^{-k}. \tag{5}$$

For a given target P_b, we use (4) as an equality, replace $\mu^{(i)}$ with μ_{req}, and derive μ_{req} as a function of k. This function along with (5) is used to approximate μ_{req} as a function of R, say $g(R)$. The approximation can be done by simple curve fitting. Finally, using $\mu_{\text{req}} = g(R)$ and (3), one can express the required SNR as a function of R:

$$\text{SNR}_{\text{req}} = \frac{R}{W} g(R) \stackrel{\text{def}}{=} \frac{f(R)}{W}. \tag{6}$$

In the case of AOM, $f(R)$ can be well-approximated (less than 1% fitting error) by the posynomial function[5] aR_i^b, for some real-valued coefficients $a > 0$ and $b > 1$. On the other hand, in the case of VPG, $g(R)$ is a constant that is equal to μ_{req} (e.g., $g(R) = 14.8$ for $M = 2$), and therefore, SNR_{req} is simply a linear function of R. This linearity between R and SNR_{req} has been the underlying assumption in all previous adaptive rate/power control schemes for OM-based CDMA networks. We now know that this assumption does not hold for AOM.



(a) Required SNR versus data rate.

(b) Rate enhancement of AOM over VPG.

(c) Energy consumption of AOM relative to VPG.

Fig. 4. Performance of AOM and VPG for a single link.

[5]The definition of a posynomial can be found in Appendix A.

Using the relationships between R and SNR_{req}, we are now in a position to compare the performance of AOM with VPG for the single-link case. Figure 4 demonstrates several performance metrics obtained using $Z = W$ and $R_{\text{max}} = W/2$. Part (a) of the figure depicts SNR_{req} versus the normalized rate R/W. It is clear that for all $R < R_{\text{max}}$, AOM requires a significantly less SNR than VPG to achieve a certain data rate. Such an improvement essentially reflects a *power gain*. Equivalently, AOM achieves a much higher rate than VPG for the same SNR_{req} (i.e., rate gain). Part (b) of the figure shows the relative rate enhancement of AOM over VPG versus the SNR. It is shown that the rate advantage of AOM over VPG increases as the SNR decreases, and is very significant in the low SNR regime. Note that when SNR ≥ 8.7 dB, the link operates at R_{max}, and AOM uses the same modulation order as VPG, i.e., there is no rate improvement. Part (c) of the figure shows the energy-per-data bit (E_b) consumption of AOM relative to that of VPG versus the SNR. E_b is defined as the transmission power divided by R. The figure shows that AOM consumes much less E_b than VPG in the low SNR regime. The E_b consumption of AOM increases as the SNR increases until the maximum rate is reached, at which AOM consumes the same E_b as VPG.

In the above discussion, we permitted the modulation order M to take any real positive value; however, in real life, M is restricted to a finite set [6]. Nonetheless, we evaluate the potential gains without this additional constraint to serve as an upper bound on the performance of AOM in practice.

III. Joint Rate/Power Optimization for AOM Systems

The analysis presented in the previous section focused on the single-user case. For a network of users, increasing one user's power increases that user's SNR, and consequently its rate. However, this comes at the expense of the SNR for other users, whose data rates must now be reduced to combat the added interference. Determining the best powers and rates that optimize a given objective function (e.g., network throughput) is not straightforward. The goal of this section is to define objective functions and derive policies that optimize them for the case of a network of users (i.e., multiuser case).

We study two throughput-oriented objective functions: (1) minimizing the maximum service time, and (2) maximizing the sum of users' transmissions rates. The two functions differ in two aspects: the time scale at which rate adaption is carried out and the required hardware.

A. Minimizing the Maximum Service Time

Let L_i be the load (in bits) to be transmitted over link i, $i \in I$, where I is the set of active links in the network. Recall that R_i is the data rate (in bits/sec) for link i. The service time for link i, denoted by S_i, is L_i/R_i. A scheme that minimizes the maximum service time $S_{\text{max}} = \max\{S_i,\ i \in I\}$ has the advantage of being easy to integrate in many current wireless network standards. For example, the access point (AP) of an IEEE 802.11 WLAN (or the Piconet controller of an IEEE

[6] The burden of demodulation for high values of M can be alleviated by using the Fast Walsh Transform method [2], which requires only $M \log_2 M$ real additions and subtractions.

802.15.3 WPAN) can utilize its polling medium access mechanism to measure the channel gains between the AP and each mobile node, and to probe nodes about their loads. Using channel gains and load values, the AP can compute the optimum powers and rates that minimize S_{max}. A scheme that minimizes S_{max} does not require users to receive any feedback from the AP while transmitting, i.e., only one transceiver is required at a node. Furthermore, rate adaptation is carried out on a per-packet basis (i.e., the whole packet is transmitted at one rate), which is practical for current wireless networks standards [29].

Given the channel gains and the loads L_i $\forall i \in I$, the goal is to find the transmission powers and rates (i.e., $P_t^{(i)}$ and R_i, $\forall i \in I$) so as to minimize S_{max}. Formally, this problem is stated as follows:

$$\begin{cases} \underset{\{R_i, P_t^{(i)},\, i\in I\}}{\text{minimize}} \left\{ \max_{i\in I} \frac{L_i}{R_i} \right\} \\ \text{subject to:} \\ \frac{h_{ii} P_t^{(i)}}{\sum_{j\in I-\{i\}} h_{ji} P_t^{(j)} + P_{\text{thermal}}} \geq \frac{f(R_i)}{W}, \quad \forall i \in I \\ 0 \leq P_t^{(i)} \leq P_{\text{max}}, \quad \forall i \in I \\ R_{\text{min}} \leq R_i \leq R_{\text{max}}, \quad \forall i \in I \end{cases} \tag{7}$$

The first constraint reflects the BER requirement of link i, since it mandates that i's SNR be greater than or equal to $\frac{f(R_i)}{W} = \text{SNR}_{\text{req}}$ (see (6)). $\frac{f(R_i)}{W}$ is equal to $\frac{R_i}{W}\mu_{\text{req}}$ for VPG and is approximated by $a(R_i/Z)^b(Z/W)$ for AOM, where a and b are two constants whose values are obtained from the fitting of $f(R)$. In our simulations, $a \approx 9.8$ and $b \approx 1.2$, with less than 1% fitting error. Although the formulation in (7) assumes the same minimum rate, maximum rate, and maximum power constraints for all nodes, this can be easily extended to handle the case of node-specific constraints. Note that this formulation is applicable to both PTP and MultiPTP networks.

Proposition 1: The optimization problem in (7) is a generalized geometric program (GGP). This GGP can be transformed into a geometric program (GP), which itself can be transformed into a nonlinear convex program[7].

Proof: With simple algebraic manipulations, (7) can be expressed as:

$$\begin{cases} \underset{\{R_i, P_t^{(i)},\, i\in I\}}{\text{minimize}} \left\{ \max_{i\in I} \{L_i R_i^{-1}\} \right\} \\ \text{subject to:} \\ \left[\sum_{j\in I-\{i\}} h_{ji} P_t^{(j)} + P_{\text{thermal}} \right] \left[h_{ii} P_t^{(i)} \right]^{-1} \frac{f(R_i)}{W} \leq 1 \\ P_t^{(i)} P_{\text{max}}^{-1} \leq 1 \\ R_i R_{\text{max}}^{-1} \leq 1 \\ R_i^{-1} R_{\text{min}} \leq 1 \end{cases} \tag{8}$$

[7]See Appendix A for a brief description of GGP and GP.

where the constraints in (8) are to be satisfied for all $i \in I$. If $f(R)$ is a posynomial (see Appendix A), which is the case for both VPG and AOM, (8) is a GGP. In its current form, this GPP cannot be solve optimally and efficiently. Therefore, we make two transformations. The first one transforms the above GGP into a GP. To this end, we introduce a new auxiliary variable t such that:

$$t \geq \frac{L_i}{R_i}, \quad \forall i \in I. \tag{9}$$

With the introduction of t, (8) becomes:

$$\begin{cases} \underset{\{t, R_i, P_t^{(i)},\, i \in I\}}{\text{minimize}} \quad t \\ \text{subject to:} \\ L_i R_i^{-1} t^{-1} \leq 1 \\ \left[\sum_{j \in I - \{i\}} h_{ji} P_t^{(j)} + P_{\text{thermal}}\right] \left[h_{ii} P_t^{(i)}\right]^{-1} \frac{f(R_i)}{W} \leq 1 \\ P_t^{(i)} P_{\text{max}}^{-1} \leq 1 \\ R_i R_{\text{max}}^{-1} \leq 1 \\ R_i^{-1} R_{\text{min}} \leq 1 \end{cases} \tag{10}$$

It is obvious that (8) and (10) are equivalent forms, meaning that the powers and rates that minimize t also minimize the objective function in (8). Formulation (10) is an example of a GP, which can be easily transformed into a nonlinear convex program using a logarithmic change of variables [8]. Formally, let $z \overset{\text{def}}{=} \log t$, $x_i \overset{\text{def}}{=} \log P_t^{(i)}$, and $y_i \overset{\text{def}}{=} \log R_i$ $\forall i \in I$ (so that $t = e^z$, $P_t^{(i)} = e^{x_i}$, and $R_i = e^{y_i}$). Instead of minimizing the objective function t, we now minimize $\log t$. Also, each constraint of the form $f \leq 1$ is changed to $\log f < 0$. This results in the following (equivalent) optimization problem:

$$\begin{cases} \underset{\{z, x_i, y_i,\, i \in I\}}{\text{minimize}} \quad z \\ \text{subject to:} \\ \log \; L_i e^{-y_i} e^{-z} \leq 0 \\ \log \; \left[\sum_{j \in I - \{i\}} h_{ji} e^{x_j} + P_{\text{thermal}}\right] h_{ii}^{-1} e^{-x_i} \frac{f(e^{y_i})}{W} \leq 0 \\ \log \; e^{x_i} P_{\text{max}}^{-1} \leq 0 \\ \log \; e^{y_i} R_{\text{max}}^{-1} \leq 0 \\ \log \; e^{-y_i} R_{\text{min}} \leq 0 \end{cases} \tag{11}$$

At first, the above formulation may look more complicated than (10). However, unlike (10), (11) is a *convex* optimization problem that can be solved efficiently (see [8] for more details). Once (11) is solved for x_i and y_i, $\forall i \in I$, the optimal power and rate allocation is simply given by $P_t^{(i)} = e^{x_i}$ and $R_i = e^{y_i}$ $\forall i \in I$. ■

Proposition 1 applies to both PTP and MultiPTP networks, and also for VPG as well as AOM schemes. In the case of

MultiPTP networks, the structure of the problem can be further simplified to allow for even a faster computation of the optimal solution. The following proposition enables the subsequent derivation of this solution.

Proposition 2: The powers and rates that optimize (7) are such that the first constraint is satisfied with equality.

Proof: See Appendix B.

In MultiPTP networks, the receiver is common to all transmitters, and so the channel gains h_{ji} and h_{ii} can be simply written as h_j and h_i, respectively. Hence, utilizing Proposition 2, the optimal power and rate allocation in the case of MultiPTP networks must satisfy the following set of linear equations:

$$\frac{h_i P_t^{(i)}}{\sum\limits_{j \in I - \{i\}} h_j P_t^{(j)} + P_{\text{thermal}}} = \frac{f(R_i)}{W}, \quad \forall i \in I. \tag{12}$$

Using the same derivation methodology as in [35], (12) can be reduced to:

$$\sum_{j \in I} \frac{1}{\left(\frac{W}{f(R_j)} + 1\right)} = 1 - \frac{P_{\text{thermal}}}{P_t^{(i)} h_i \left(\frac{W}{f(R_i)} + 1\right)}, \forall i \in I. \tag{13}$$

By imposing the constraint $P_t^{(i)} < P_{\max}$ and noting that (13) is valid $\forall i \in I$, the following inequality can be obtained:

$$\sum_{j \in I} \frac{1}{\left(\frac{W}{f(R_j)} + 1\right)} \leq 1 - \frac{P_{\text{thermal}}}{\min\limits_{i \in I} \left[P_{\max} h_i \left(\frac{W}{f(R_i)} + 1\right)\right]}. \tag{14}$$

This equation determines the feasibility of a set of rates, BER requirements, and maximum power constraints. Next, we use (14) to derive the optimal solution for (7). Consider the following proposition:

Proposition 3: The powers and rates that optimize (7) are such that $\frac{L_i}{R_i} = \frac{L_j}{R_j} \; \forall \, i, j \in I$.

Proof: See Appendix C.

This proposition says that, at the optimal solution to (7), all users have the same service time (S). Hence, $R_i = L_i/S$ $\forall i \in I$. Accordingly, (14) can be written as:

$$\sum_{j \in I} \frac{1}{\left(\frac{W}{f(L_j/S)} + 1\right)} \leq 1 - \frac{P_{\text{thermal}}}{\min\limits_{i \in I} \left[P_{\max} h_i \left(\frac{W}{f(L_i/S)} + 1\right)\right]}. \tag{15}$$

The only unknown in this equation is S, and so it can be easily solved for the minimum S. Note that a unique solution always exist, since the left-hand side (LHS) of (15) is 0 at $S = \infty$, and it increases as S decreases, while the RHS is 1 at $S = \infty$, and it decreases as S decreases. In Section IV, we use (15) to show the significant performance improvement of AOM over VPG.

B. Maximizing the Sum of Users Rates

The goal of this objective function is to maximize network throughput, subject to constraints on the BER, the maximum transmission power, and the minimum and maximum transmission rates. This function, which has been the focus of much previous research, requires fast rate adaptation; for the network to operate at the optimal point, whenever a user completes the transmission of a packet, all other transmitters must update their rates in the midst of transmitting their packets. This means that users must use intra-packet rate adaptation (i.e., different portions of the same packet must be transmitted at different rates). Furthermore, maximizing the sum of rates requires users to be able to receive feedback about their new rates while transmitting, which may necessitate the use of a multiple-channel multiple-transceiver architecture. Note that the minimum-rate constraint, which has been overlooked in most previous studies, is crucial for multimedia networks; without this constraint, some users may never be allowed to transmit, particularly if they experience a "bad" channel relative to other users (i.e., their channel gains are relatively small).

The power/rate optimization problem for both AOM and VPG can be formulated as follows:

$$\begin{cases} \underset{\{R_i, P_t^{(i)},\, i \in I\}}{\text{maximize}} \quad \sum_{i \in I} R_i \\ \text{subject to:} \\ \frac{h_{ii} P_t^{(i)}}{\sum_{j \in I - \{i\}} h_{ji} P_t^{(j)} + P_{\text{thermal}}} \geq \frac{f(R_i)}{W}, \quad \forall i \in I \\ 0 \leq P_t^{(i)} \leq P_{\max}, \quad \forall i \in I \\ R_{\min} \leq R_i \leq R_{\max}, \quad \forall i \in I. \end{cases} \tag{16}$$

Unfortunately, this objective function cannot be transformed into the minimization of a posynomial as was done in the previous section. So it is not possible to formulate this problem as a GGP, a GP, or a nonlinear convex program. In fact, the problem exhibits an unknown number of local maxima, and there are no efficient algorithms to solve it optimally for the general case (i.e., PTP networks). However, in order to get a feeling of how much improvement AOM can provide over VPG, we fix one dimension of the problem, namely, the transmission powers, and limit our attention to rate optimization. Specifically, for PTP networks, we examine the case when nodes use the maximum power ($P_{\max}$). First, consider the following result.

Proposition 4: The powers and rates that optimize (16) are such that the first constraint is satisfied with equality.

Proof: The proof is similar to the one for Proposition 2, and is omitted for brevity.

If all users operate at $P_{\max}$, then from Proposition 4, it is easy to compute the users rates for both AOM and VPG by solving the following set of equations:

$$R_i = f^{-1}\left(\frac{W\ h_{ii} P_{\max}}{\sum_{j \in I - \{i\}} h_{ji} P_{\max} + P_{\text{thermal}}}\right), \ \ \forall i \in I. \tag{17}$$

For MultiPTP networks, we follow a different approach that allows us to obtain a lower bound on the achievable gain of AOM over VPG schemes. Without loss of generality, let the users in the set I be ordered according to their link-channel gains, i.e., $i < j \Rightarrow h_i \geq h_j$. It has been shown in [19] that in the case of VPG [8], the optimal solution for (16) has the following structure:

- The set of best v_1 users (I_{v_1}) operate at rate R_{max} (i.e., at the maximum-rate boundary) and their powers satisfy $h_i P_t^{(i)} = h_j P_t^{(j)} \ \forall i, j \in I_{v_1}$, i.e., they have equal *received* powers.
- The set of next v_2 best users (I_{v_2}) operate at power P_{max} (i.e., at the maximum-power boundary) and rates $R_i < R_{\text{max}}$ $\forall i \in I_{v_2}$. Note that $h_i P_t^{(i)} < h_j P_t^{(j)} \ \forall i \in I_{v_2}$ and $\forall j \in I_{v_1}$ (see [19] for more details).
- At most, there is one user U (whose order in I is $v_1 + v_2 + 1$) that operates at rate R_U and power $P_t^{(U)}$ such that $R_{\text{min}} < R_U < R_{\text{max}}$ and $P_t^{(U)} < P_{\text{max}}$. Furthermore, $h_U P_t^{(U)} < h_i P_t^{(i)}$ and $R_U < R_i \ \forall i \in \{I_{v_1} \bigcup I_{v_2}\}$.
- The remaining users, $I_{v_3} = I - I_{v_1} - I_{v_2} - \{U\}$, operate at rate R_{min} (i.e., at the minimum-rate boundary) and power $h_i P_t^{(i)} = h_j P_t^{(j)} \ \forall i, j \in I_{v_3}$, i.e., they have equal *received* powers. Furthermore, $h_i P_t^{(i)} < h_j P_t^{(j)} \ \forall i \in I_{v_3}$ and $\forall j \in \{I_{v_1} \bigcup I_{v_2} \bigcup U\}$.

Using this solution structure, we now present a proposition that will enable us to derive a novel algorithm for finding the optimal solution for VPG networks. We then show how this algorithm can be used as a heuristic for AOM networks.

Proposition 5: For VPG MultiPTP networks, the optimal solution to (16) is such that there is only one element in the set $\{I_{v_2} \bigcup U\}$, i.e., some users operate at the maximum-rate boundary, others operate at the minimum-rate boundary, and only one user operates at a rate in between these two boundaries.

Proof: See Appendix D.

This optimal solution is intuitive and agrees with previously reported information theoretic results [38]; if there is no constraint on the maximum rate, the system throughput is maximized while simultaneously satisfying each user's minimum-rate constraint only when the best-channel user is allowed to transmit at a power larger than the one required for it to achieve R_{min}. If there is a constraint on the maximum rate, allowing only the best user to increase his power may not achieve the maximum network throughput. The reason is that the best user cannot utilize any extra power beyond the one required to achieve R_{max}. Hence, the optimal policy will then be that some best-channel users operate at R_{max} (without using P_{max}), some bad-channel users operate at R_{min}, and at most one user operates at a rate that is between R_{max} and R_{min}.

Based on Proposition 5, the optimal solution for VPG networks can be found by assigning rate R_{max} to the maximum possible number of users such that the feasibility condition (14) is not violated, and then assigning to the next best user the maximum power at which (14) is satisfied with equality. The details of the algorithm are as follows:

1) Assign rate R_{min} $\forall i \in I$ and check the feasibility condition in (14); if this condition is not satisfied, then there is no solution to this problem; otherwise go to the next step.
2) Assign rate R_{max} to the best user in I, say user j, and check the feasibility condition in (14); if satisfied, then set $I = I - \{j\}$ and repeat this step; otherwise, go to the next step.

[8]The authors in [19] did not consider a minimum-rate constraint; however, their results extend to the case when $R_{\text{min}} > 0$.

3) Find the maximum power ($P_{allowed}$) that j can use such that (14) is satisfied with equality; the transmission power of j is then given by $P_j = \min\{P_{allowed}, P_{\max}\}$.

This rate/power assignment (RPA) algorithm gives an optimal solution for VPG. We now explain the intuition behind using the same algorithm as a *heuristic* for AOM. The main idea is to replace the objective function in (16) by a slightly different but related objective function, and then measure the actual throughput under this new function. First, note that in the case of AOM, $f(R_i)$, which was shown in Part (a) of Figure 4, can be well-approximated by a second-degree polynomial in R_i, say $a_1 R_i^2 + b_1 R_i + c_1$, which can be written as $\big(a_1(R_i + b_2)^2 + c_2\big)$ for some coefficients a_1, b_1, c_1, b_2, and c_2. Of course such an approximation has a higher fitting error than the posynomial fitting chosen earlier $\big(\text{i.e., } aR_i^b\big)$. Let $O_i \stackrel{\text{def}}{=} (R_i + b_2)^2$, $O_{\min} \stackrel{\text{def}}{=} (R_{\min} + b_2)^2$, and $O_{\max} \stackrel{\text{def}}{=} (R_{\max} + b_2)^2$, and replace the objective function in (16) by $\sum_{i \in I} O_i$. Then, the optimization problem becomes:

$$\begin{cases} \underset{\{O_i, P_t^{(i)},\, i \in I\}}{\text{maximize}} \quad \sum\limits_{i \in I} O_i \\ \text{subject to:} \\ \dfrac{h_{ii} P_t^{(i)}}{\sum\limits_{j \in I - \{i\}} h_{ji} P_t^{(j)} + P_{\text{thermal}}} \geq \dfrac{a_1 O_i + c_2}{W}, \quad \forall i \in I \\ 0 \leq P_t^{(i)} \leq P_{\max}, \qquad \forall i \in I \\ O_{\min} \leq O_i \leq O_{\max}, \qquad \forall i \in I \end{cases} \tag{18}$$

This formulation has a similar structure to the one of VPG. Since RPA finds the optimal solution to VPG, it can also find the optimal solution to (18) (a_1 and c_2 are constants that do not affect the optimization algorithm). This means that RPA can be used to maximize $\sum_{i \in I}(R_i + b_2)^2$. The powers and rates that maximize $\sum_{i \in I}(R_i + b_2)^2$ are not necessarily equal to the ones that maximize $\sum_{i \in I} R_i$. However, we expect them to be close. In this sense, RPA can be used as a heuristic method to maximize $\sum_{i \in I} R_i$. The simulation results in Section IV show that based on this heuristic, AOM provides significant performance advantages over VPG.

IV. Performance Evaluation

A. Simulation Setup

In this section, we evaluate the performance of AOM and contrast it with that of VPG [19]. Our results are based on numerical experiments conducted using MATLAB. Our performance metrics include the service time (S)[9], the sum of users rates, and the average energy consumption per bit (E_b), defined as $\frac{\sum_{i=1}^N P_i}{\sum_{i=1}^N R_i}$. Note that E_b is a more significant measure than the average transmission power. In fact, it is misleading to compare the average transmission power of two systems that transmit at different data rates, as the cost of transmitting a certain number of bits depends on both the transmission power and the rate. In some cases, we also study the throughput and energy fairness indexes $I_R = \frac{\left(\sum_{i=1}^N R_i\right)^2}{N \sum_{i=1}^N R_i^2}$

[9] At the optimal solution for the first objective function, all users have the *same* service time S (see Proposition 3).

and $I_E = \frac{\left(\sum_{i=1}^{N}(P_i/R_i)\right)^2}{N\sum_{i=1}^{N}(P_i/R_i)^2}$, respectively [20]. The fairer the system, the higher are the values of I_R and I_E. I_R measures the "equality" of users allocation of throughput. If all users get the same amount of throughput, then the fairness index is 1, and so the system is 100% fair. As the discrepancy in throughput increases, I_R decreases. A scheme that favors only few users has a fairness index close to zero. I_E measures the discrepancy in the amount of energy each user invests in delivering one bit of information. Typically, a system designer would like this per-bit energy to be equal for all users to extend the lifetime of users' batteries. To simulate the channel gains, we assume the two-ray propagation model with a path loss factor of 4. Note, however, that the problem formulation does not depend on *how* the channel attenuation matrix is generated, i.e., any other fading model can be used. The total bandwidth of the system (i.e., the chip rate) is $W = 1$ MHz. We let $P_{\max} = 20$ dBm.

B. Point-to-Point Networks

In this scenario, N transmitting nodes are randomly placed across a square area of length 600 meters. For each transmitter j, the receiving node i is placed randomly within a circle of radius 100 meters that is centered at j. Given the location of the N receivers and N transmitters, the channel attenuation the channel attenuation between any pairs of nodes i and j is computed using the the two-ray propagation model with attenuation factor equals to 4. The matrix H is then formed with entries h_{ij}. Whenever the solution set is empty for the generated H (i.e., $R_{\min}$ cannot be achieved for all users), a new set of transmitters and receivers are randomly generated. The maximum-rate constraint $R_{\max}$ is chosen such that the modulation order M used in VPG is equal to 16, which is the *minimum* M used in AOM. For this experiment, we let $R_{\min} = R_{\max}/100$.

Number of Node Pairs (N)	Scheme	Minimize Max S_i		Maximize $\sum R_i$			
		S (sec)	E_b (microjoules/bit)	$\sum R_i$ (Mbps)	E_b (microjoules/bit)	I_R	I_E
20	VPG	73.6	1.86	1.83	1.09	0.50	0.21
	AOM	25.5	0.45	2.08	0.96	0.58	0.30
30	VPG	137.5	0.58	2.57	1.17	0.47	0.51
	AOM	69.3	0.34	2.94	1.02	0.55	0.58

TABLE I

PERFORMANCE COMPARISON BETWEEN AOM AND VPG IN PTP NETWORKS.

The performance of AOM and VPG is shown in Table I. The results are reported for $N = 20$ and $N = 30$ based on the average of 100 independent realizations of the matrix H. For the first objective function, (i.e., minimizing the maximum service time), all nodes are assumed to have 1 Mbits of data. Although a randomly generated workload is more practical, the choice of equal workloads is meant to facilitate the discussion. For $N = 20$ and $N = 30$, AOM achieves a reduction in S by 65.4% and 50%, respectively, while simultaneously achieving about 75% and 42% energy savings, respectively.

The reason for this considerable improvement can be explained as follows. From Proposition 3, we know that at the optimal powers and rates, all users have the same S. Since users have the same load (1 Mbits), the optimal solution is when all users transmit at the *same* rate. This rate must be chosen to accommodate the worst-channel user (i.e., lowest SNR). AOM, as Figure 4 shows, has a significant performance advantage over VPG at *low* SNR values; thus providing a smaller service time and a much lower energy consumption than VPG.

For the second objective function (i.e., maximizing the sum of users rates), the optimal solution in PTP networks is unknown; however, to provide a feeling of what the AOM improvement is, we let all users transmit at P_{max}, and compute the corresponding optimal rates using (17). For both $N = 20$ and $N = 30$, AOM achieves about 15% increase in throughput, 13% saving in energy, and about 16% improvement in I_R relative to VPG. The improvement in I_E for $N = 20$ is particulary significant (about 42%). Such an improvement is justified by noting that AOM achieves a significant throughput gain for low-rate (low-SNR) links, sometimes twice that of VPG, but provides little gain for high-rate links. This has a negligible impact on throughput, but has a significant impact on I_E.

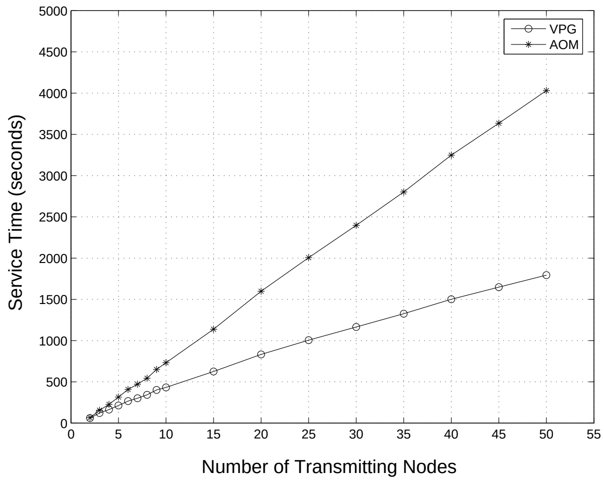
C. Multipoint-to-Point Networks

In this section, we consider N transmitting nodes that are randomly placed within a square area of length 200 meters. The common receiver is placed at the center of the square. Given the location of the nodes, the channel attenuation matrix H. Similar to the PTP case, whenever the solution set is empty for the generated H, a new set of transmitters is randomly generated. The results are obtained based on the average of 100 independent realizations of the matrix H.

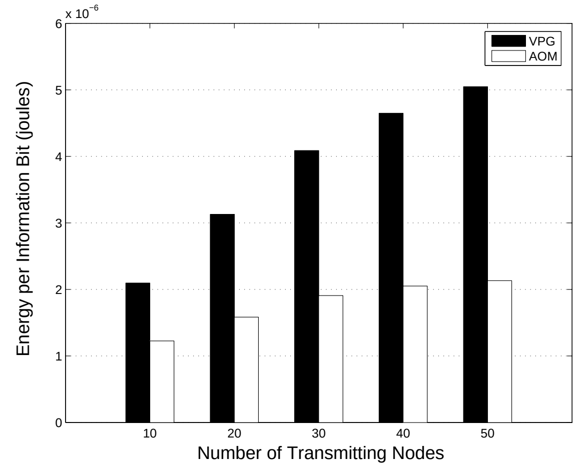
For the first objective function, the workload at each transmitter is selected randomly between 1 and 20 Mbits. As before, R_{max} is chosen such that the modulation order M used in VPG is equal to 16. Figure 5 depicts the performance of AOM and VPG for the first objective function. Part (a) of the figure depicts the service time S versus N. It is shown that as N exceeds 10, AOM achieves considerably lower S than VPG. For example, when $N = 50$, S under AOM is only 45% of S under VPG. It is also shown that S under both AOM and VPG increases with N. This is expected since as N increases, the multiple access interference (MAI) also increases, and users are forced to transmit at lower rates, which increases their service times.

Note that for VPG, the S-versus-N curve is approximately linear, while for AOM, the slope of that curve decreases slightly with N. This can be explained by examining (15). The RHS of (15) is close to 1, as P_{thermal} is typically very small. In the case of VPG, $f(L_i/S) = \mu_{\text{req}} L_i/S$, $WS/L_i\mu_{\text{req}} \gg 1$, and so the LHS of (15) can be well-approximated by $\frac{\mu_{\text{req}}}{S}\sum_{i\in I} L_i \approx \frac{\mu_{\text{req}}}{S} N L_{ave}$, where L_{ave} is the expected value of L_i. This explains why S increases almost linearly with N. For the AOM case, $f(Li/S) = a(L_i/S)^b$ for some coefficients $a > 0$ and $b > 1$. It is easy to show that the S-versus-N curve can be approximated by $S \approx cN^{1/b}$, for some coefficients $c > 0$. Thus, its derivative (or slope) decreases with N.

Part (b) of Figure 5 depicts E_b versus N. It shows that in addition to reducing the service time, AOM achieves a significant energy saving over VPG. For example, for $N = 50$, AOM energy expenditure is less than 40% that of VPG.



(a)



(b)

Fig. 5. Performance of AOM and VPG based on the minimization of the maximum service time in MultiPTP networks.

Next, we study the impact of increasing P_{thermal} on the service time S. Figure 6 shows S as a function of P_{thermal} for $N = 30$. The workload is generated as in Figure 5. For all values of P_{thermal}, AOM consistently shows a good improvement over VPG. For both AOM and VPG, however, S starts to increase exponentially when P_{thermal} exceeds -60 dBm. The reason is that at this value, P_{thermal} becomes comparable to the maximum received powers for bad-channel users. Hence, the SNR of the users deteriorates significantly, causing a fast drop in their rates, and a corresponding dramatic increase in S.

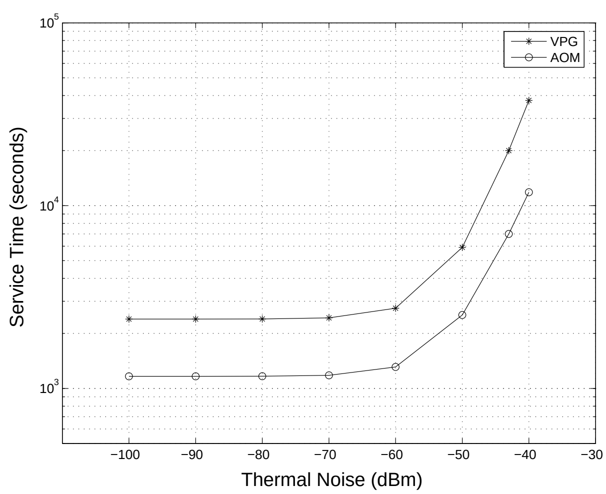
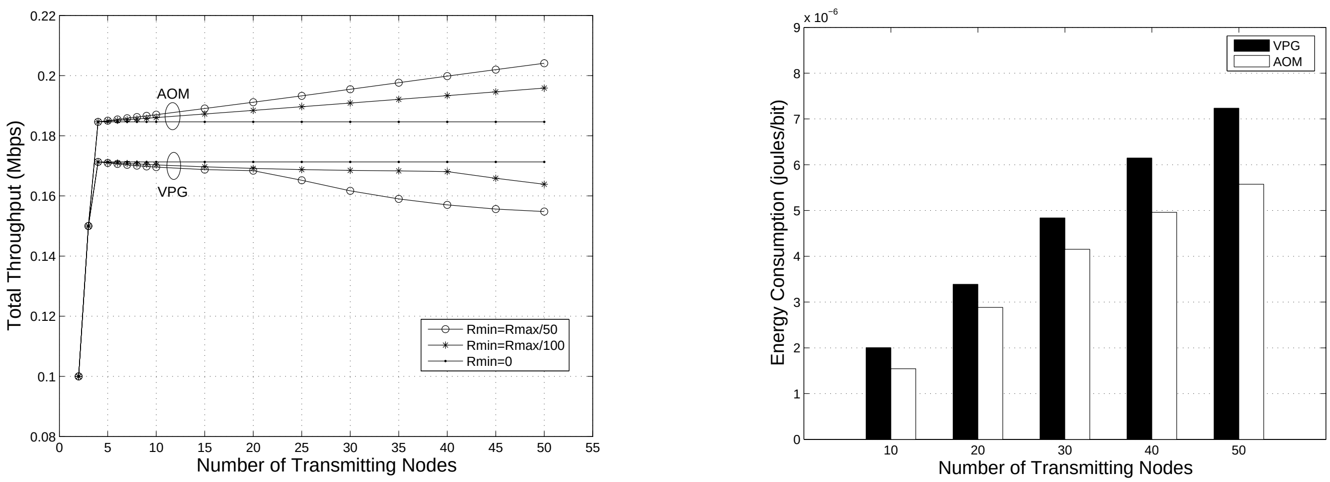


Fig. 6. Service time S of AOM and VPG in MultiPTP networks as a function of P_{thermal}.

In the case of the second objective function (i.e., maximizing the sum of users rates), we set the maximum modulated bit rate Z to $W/5$. As before, $R_{\max}$ is chosen such that the modulation order M used in VPG is equal to 16 (i.e., $R_m/R = 4$), so $R_{\max} = W/20$. Part (a) of Figure 7 depicts the throughput performance versus N for three different values of $R_{\min}$ ($R_{\max}/50$, $R_{\max}/100$, and zero). Recall that the used RPA algorithm is optimal for VPG , but is only a heuristic for AOM, so the results in Figure 7 represent a lower bound on the achievable gain of AOM over VPG. Several observations can be made based on this figure.



(a) (b)

Fig. 7. Performance versus N under the throughput maximization criterion for MultiPTP networks.

First, AOM achieves considerably more throughput than VPG; e.g., for $R_{\text{min}} = R_{\text{max}}/50$ and $N = 50$, AOM achieves about 30% more throughput than VPG. This is because for any power allocation vector, AOM enables higher rates than VPG. Second, in the cases of $R_{\text{min}} = R_{\text{max}}/50$ and $R_{\text{min}} = R_{\text{max}}/100$, as N increases, the throughput for AOM increases, while the throughput for VPG decreases. This can be explained as follows. For VPG, as N increases, more bad-channel users are required to operate at R_{min}. To enable this, other (good-channel) users must decrease their powers (and consequently their rates) to reduce the MAI. The increase in the total throughput due to a higher number of bad-channel users does *not* offset the decrease in the throughput of the good-channel users. Therefore, the overall effect is a slight reduction in network throughput. This is not the case, however, for AOM. Simulation results indicate that the increase in the total throughput due to more bad-channel users is higher than the decrease in the throughput of the good-channel users. This can be justified as follows. Unlike VPG, AOM uses higher OM orders at low data rates and thus requires much less SNR than VPG to achieve R_{min}. Thus, good-channel users do *not* need to reduce their powers (and their rates) considerably to accommodate the new users, and so the reduction in the throughput of the good-channel users is not considerable (when compared to the VPG case). The overall effect is a slight increase in network throughput. The throughput of AOM increases with N until the RPA is unable to find a feasible solution.

Another observation is that as R_{min} increases, the throughput for VPG decreases, while the throughput for AOM increases. So the throughput gain of AOM over VPG goes up with R_{min}. This can be explained as follows. Increasing R_{min} tightens the constraints (i.e., reduces the solution space), and this results in a lower throughput whenever RPA is optimal. This is exactly what happens in the VPG case since RPA is optimal for VPG. But since RPA is *heuristic* for AOM, we conjecture that its performance becomes closer to the optimal one as R_{min} increases, and so the throughput increases.

The last point to note about Figure 7-(a) is that for $R_{\text{min}} = 0$, both AOM and VPG are almost linear. The reason is that when $R_{\text{min}} = 0$, RPA allocates powers only to good-channel users until the network "saturates," i.e., v_1 users are assigned R_{max} and only one user is assigned the rest of the power such that (14) is satisfied. Adding more users has no impact once (14) is satisfied.

As in the PTP case, the throughput advantage of AOM over VPG comes with energy savings. Part (b) of Figure 7 depicts the energy consumption of AOM and VPG as a function of N for $R_{\text{min}} = R_{\text{max}}/50$. This figure shows that AOM achieves a significant energy saving over VPG (up to 25%).

Next, we study the fairness properties of AOM and VPG. Part (a) and (b) of Figure 8 depict I_R and I_E, respectively, as a function of N (recall that the fairer the system, the higher are the values of I_R and I_E). The results are for $R_{\text{min}} = R_{\text{max}}/50$. It can be observed that relative to VPG, AOM can improve I_R and I_E up to 21% and 30%, respectively.

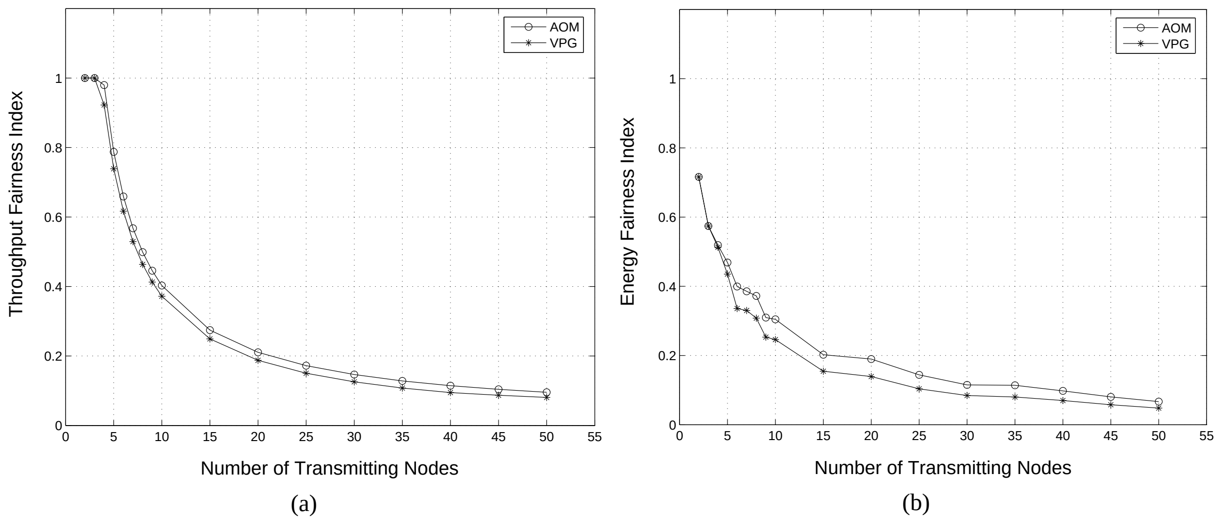


Fig. 8. Fairness versus N under the throughput maximization criterion for MultiPTP networks.

Finally, we study the effect of varying the minimum processing gain (PG) by varying R_{max}. We fix R_{min} in this experiment at $W/500$. Figure 9 shows the performance of AOM and VPG as a function of the minimum PG. It can be observed that the sum of rates decreases as the PG increases for both AOM and VPG. This agrees with the previous intuition that reducing R_{max} tightens the solution space, and so decreases the achieved maximum. Furthermore, it not difficult to notice that RPA favors higher values of R_{max}.

V. Conclusions and Open Issues

In this paper, we investigated the potential performance gains of using adaptive orthogonal modulation (AOM) in multirate CDMA networks. We showed that, relative to a variable processing gain (VPG) system that uses fixed orthogonal modulation (OM) order, AOM can significantly increase the network throughput while simultaneously reducing energy consumption. We studied the problem of optimal joint rate/power control for AOM-based systems under two objective functions: minimizing the maximum service time and maximizing the sum of users rates. For the first objective function, we showed that the optimization problem can be formulated as a GGP, which can be transformed into a nonlinear convex

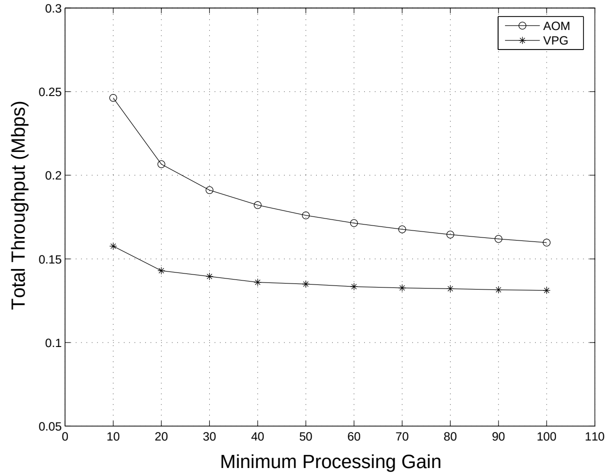


Fig. 9. Throughput in MultiPTP networks as a function of the minimum processing gain (varied through R_{max}).

program, and be solved optimally and efficiently. In the case of the second objective function, we obtained a lower bound on the achievable gain of AOM over fixed-modulation schemes. Unlike previous work on adaptive transmission, which have focused mainly on cellular networks, ours is applicable to both PTP and MultiPTP networks.

In PTP networks, our results show that, when compared with fixed OM order VPG schemes, AOM can achieve more than 50% improvement in the service time and, simultaneously, more than 40% reduction in energy consumption. In MultiPTP networks, we derived a simple algorithm for finding the optimal powers and rates for VPG, and explained the intuition behind using that algorithm as a heuristic for AOM. Our results show that the achievable throughout gain can be up to 30% compared to VPG. Furthermore, AOM achieves more than 45% reduction in the service time relative to VPG.

In our analysis, we let the modulation order M to take real positive value. However, in reality, M is restricted to a finite set. Our future work will focus on studying the impact of restricting M to a finite set of values.

AOM is still a newly explored area of research. Several challenges remain to be addressed, including finding the optimal solution for maximizing the sum of rates for AOM in MultiPTP networks, the optimal algorithm for maximizing the sum of rates for VPG and AOM in PTP networks, and closed-form approximations to the optimal solutions. In addition to solving for these theoretical limits, our future work will focus on how to integrate these algorithms within current wireless networks protocols.

Appendix

A. Geometric Programming

Let $x_1, \ldots, x_n$ be n variables in $\mathbb{R}^+$, and let $\mathbf{x} \stackrel{\text{def}}{=} (x_1, \ldots, x_n)$. A function f is called a *posynomial* in $\mathbf{x}$ if it can be written in the form $f(x_1, \ldots, x_n) = \sum_{k=1}^{K} c_k x_1^{a_{1k}} x_2^{a_{2k}} \ldots x_n^{a_{nk}}$, where $c_k \geq 0$ and $a_{ik} \in \mathbb{R}$. If $K = 1$, then f is called a *monomial* function. A GP is an optimization problem of the form [8]:

$$\begin{cases} \underset{\{x_i,\, i\in I\}}{\text{minimize}} \;\; f_0(\mathbf{x}) \\ \text{subject to:} \\ f_i(\mathbf{x}) \le 1, \qquad i = 1, \ldots, v \\ g_i(\mathbf{x}) = 1, \qquad i = 1, \ldots, u \\ x_i \ge 0, \qquad i = 1, \ldots, n \end{cases} \tag{19}$$

where $f_0, \ldots, f_v$ are posynomial functions and $g_1, \ldots, g_u$ are monomial functions. A function f is a *generalized posynomial* if it can be formed by the addition, multiplication, positive (fractional) power, or maximum of posynomials [7]. A GGP is an optimization problem of the form (19), where $f_0, \ldots, f_v$ are generalized posynomial functions and $g_1, \ldots, g_u$ are monomial functions.

B. Proof of Proposition 2

This proof is by contradiction. Denote the assigned powers and rates by the vectors $\mathbf{P}_t$, and $\mathbf{R}$, where $\mathbf{P}_t \stackrel{\text{def}}{=} (P_t^{(1)}, \ldots, P_t^{(N)})$ and $\mathbf{R} \stackrel{\text{def}}{=} (R_1, \ldots, R_N)$. Let $(\mathbf{P}_t^o, \mathbf{R}^o)$ be the optimal power and rate allocation that optimize (7), i.e., $\max_{i\in I}\left\{\frac{L_i}{R_i^o}\right\} \le \max_{i\in I}\left\{\frac{L_i}{R_i}\right\}$ for any feasible $(\mathbf{P}_t, \mathbf{R})$. Given $(\mathbf{P}_t^o, \mathbf{R}^o)$, suppose that one of the equalities, e.g., the mth link, in the first constraint in (7) is not satisfied, i.e.,

$$\frac{h_{mm} P_t^{o(m)}}{\sum_{j\in I-\{m\}} h_{jm} P_t^{o(j)} + P_{\text{thermal}}} > \frac{f(R_m^o)}{W}. \tag{20}$$

The LHS of the first constraint in (7) is a strictly increasing function of $P_t^{(i)}$ and is a strictly decreasing function of $P_t^{(j)}$ for $j \neq i$, while the RHS is a strictly increasing function of R_i. Hence, there must be some power decrement $-\triangle P < 0$ for link m and some rate increment $\triangle R > 0$ for all the links, that makes the allocation $(\mathbf{P}_t^{o'}, \mathbf{R}^{o'})$, where $\mathbf{P}_t^{o'} = (P_t^{o(1)}, \ldots, P_t^{o(m-1)}, P_t^{o(m)} - \triangle P, P_t^{o(m+1)}, \ldots, P_t^{o(N)})$ and $\mathbf{R}^{o'} = (R_1^o + \triangle R, \ldots, R_N^o + \triangle R)$, a feasible solution to (7). That is, the following inequalities are still satisfied under $(\mathbf{P}_t^{o'}, \mathbf{R}^{o'})$:

$$\frac{h_{mm}(P_t^{o(m)} - \triangle P)}{\sum_{j\in I-\{m\}} h_{jm} P_t^{o(j)} + P_{\text{thermal}}} \ge \frac{f(R_m^o + \triangle R)}{W}, \tag{21}$$

$$\frac{h_{ii} P_t^{o(i)}}{\sum_{j\in I-\{i\}-\{m\}} h_{ji} P_t^{o(j)} + h_{mi}(P_t^{o(m)} - \triangle P) + P_{\text{thermal}}} \ge \frac{f(R_i^o + \triangle R)}{W} \quad \forall i \in I - \{m\}. \tag{22}$$

Under $(\mathbf{P}_t^{o'}, \mathbf{R}^{o'})$, we have $\max_{i\in I}\left\{\frac{L_i}{R_i^o + \triangle R}\right\} < \max_{i\in I}\left\{\frac{L_i}{R_i^o}\right\}$. This is a contradiction to the optimality assumption that $\max_{i\in I}\left\{\frac{L_i}{R_i^o}\right\} \le \max_{i\in I}\left\{\frac{L_i}{R_i}\right\}$ for any feasible $(\mathbf{P}_t, \mathbf{R})$. Therefore, the assumption that there is a link that does not satisfy the equality of the first constraint in (7) can not be true.

C. Proof of Proposition 3

This proof is by contradiction. Denote the optimal powers and rates by the vectors $\mathbf{P}_t^o$, and $\mathbf{R}^o$, respectively, i.e., $\max_{i\in I}\left\{\frac{L_i}{R_i^o}\right\} \le \max_{i\in I}\left\{\frac{L_i}{R_i}\right\}$ for any feasible $(\mathbf{P}_t,\mathbf{R})$. Suppose $\max_{i\in I}\left\{\frac{L_i}{R_i^o}\right\} > \min_{i\in I}\left\{\frac{L_i}{R_i^o}\right\}$. Assume that the transmission time of the mth link is the minimum among all users, i.e., $\frac{L_m}{R_m^o} = \min_{i\in I}\left\{\frac{L_i}{R_i^o}\right\}$. The LHS of the first constraint in (7) is a strictly increasing function of $P_t^{(i)}$ and is a strictly decreasing function of $P_t^{(j)}$ for $j\neq i$, while the RHS is a strictly increasing function of R_i. Hence, there must be some power decrement $-\triangle P<0$ and some small rate decrement $-\triangle R_1<0$ for link m, and some small rate increment $\triangle R_2>0$ for all the other users, that makes the allocation $(\mathbf{P}_t^{o'},\mathbf{R}^{o'})$, where $\mathbf{P}_t^{o'} = (P_t^{o(1)},\ldots,P_t^{o(m-1)},P_t^{o(m)}-\triangle P,P_t^{o(m+1)},\ldots,P_t^{o(N)})$ and $\mathbf{R}^{o'} = (R_1^o+\triangle R_2,\ldots,R_{m-1}^o+\triangle R_2,R_m^o-\triangle R_1,R_{m+1}^o+\triangle R_2,\ldots,R_N^o+\triangle R_2)$, a feasible solution to (7). That is, under $(\mathbf{P}_t^{o'},\mathbf{R}^{o'})$, the following inequalities are still satisfied:

$$\frac{h_{mm}(P_t^{o(m)}-\triangle P)}{\sum_{j\in I-\{m\}} h_{jm}P_t^{o(j)}+P_{\text{thermal}}} \ge \frac{f(R_m^o-\triangle R_1)}{W}, \tag{23}$$

$$\frac{h_{ii}P_t^{o(i)}}{\sum_{j\in I-\{i\}-\{m\}} h_{ji}P_t^{o(j)}+h_{mi}(P_t^{o(m)}-\triangle P)+P_{\text{thermal}}} \ge \frac{f(R_i^o+\triangle R_2)}{W} \quad \forall i\in I-\{m\}. \tag{24}$$

The small rate variations in $\mathbf{R}^{o'}$ is in the sense that $\frac{L_m}{R_m^o-\triangle R_1} \le \max_{i\in I-\{m\}}\left\{\frac{L_i}{R_i^o+\triangle R_2}\right\}$. Under $(\mathbf{P}_t^{o'},\mathbf{R}^{o'})$, we have $\max_{i\in I}\left\{\frac{L_i}{R_i^o}\right\} = \max_{i\in I-\{m\}}\left\{\frac{L_i}{R_i^o}\right\} > \max_{i\in I-\{m\}}\left\{\frac{L_i}{R_i^o+\triangle R_2}\right\} = \max\left\{\max_{i\in I-\{m\}}\left\{\frac{L_i}{R_i^o+\triangle R_2}\right\},\frac{L_m}{R_m^o-\triangle R_1}\right\}$. This is a contradiction to the optimality assumption that $\max_{i\in I}\left\{\frac{L_i}{R_i^o}\right\} \le \max_{i\in I}\left\{\frac{L_i}{R_i}\right\}$ for any feasible $(\mathbf{P}_t,\mathbf{R})$. Therefore, it must be that $\max_{i\in I}\left\{\frac{L_i}{R_i^o}\right\} = \min_{i\in I}\left\{\frac{L_i}{R_i^o}\right\}$.

D. Proof of Proposition 5

Consider two networks A and B. Network A has v_1 elements in I_{v_1}, v_2 (where $v_2>1$) elements in I_{v_2}, one element in U, and v_3 elements in I_{v_3}, where I_{v_1}, I_{v_2}, U, and I_{v_3} are as defined in Section III-B. Such allocation of powers and rates adheres to the optimal structure proved in [19]. Network B has v_1 elements in I_{v_1}, only one element in the set $I_{v_2}^{'} \stackrel{\text{def}}{=} \{I_{v_2}\bigcup U\}$, and v_3 elements in I_{v_3}. Our goal is to show that network B always has a higher throughput than A.

Consider network B. Utilizing (17), and assuming that P_{thermal} is small compared to the MAI [10], the throughput of this network is:

$$T_B = v_1R_{\max}+v_3R_{\min}+\frac{W}{\mu_{\text{req}}}\frac{h_uP_u}{v_1P_{rB}^{v_1}+v_3P_{rB}^{v_3}}, \tag{25}$$

where h_u and P_u are the channel gain and transmission power of the single element of $I_{v_2}^{'}$, $P_{rB}^{v_1}$ is the received power of elements in I_{v_1}, $P_{rB}^{v_3}$ and is the received power of the elements in I_{v_3}.

[10] This assumption is quite reasonable in CDMA networks [47].

For network A, the transmission powers are different, and so is the MAI. Therefore, users in I_{v_1} must increase or decrease their powers so as to attain their rates (R_{max}) and to fulfill their BER constraints. The new received powers $P_{r_A}^{v_1}$ must be such that the SNR of users in I_{v_1} in network A is the same as their SNR in network B. Similarly, users in I_{v_3} must increase or decrease their powers to $P_{r_A}^{v_3}$ to maintain the same SNR. For the SNR of users in I_{v_1} to stay the same, the following must hold:

$$\frac{P_{r_A}^{v_1}}{(v_1-1)P_{r_A}^{v_1}+v_3P_{r_A}^{v_3}+\sum\limits_{j\in I'_{v_2}} h_jP_j} = \frac{P_{r_B}^{v_1}}{(v_1-1)P_{r_B}^{v_1}+v_3P_{r_B}^{v_3}+h_uP_{\text{u}}}, \tag{26}$$

It is quite easy to verify that if $P_{r_A}^{v_1}=\alpha P_{r_B}^{v_1}$ and $P_{r_A}^{v_3}=\alpha P_{r_B}^{v_3}$, where $\alpha=\sum_{j\in I'_{v_2}} h_jP_j/h_uP_{\text{u}}$, then (26) will be satisfied. It can also be shown that the same value of α results in equal SNR of users in I_{v_3} for networks A and B. Having decided the values of $P_{r_A}^{v_1}$ and $P_{r_A}^{v_3}$, we are now able to express the throughput of network A as:

$$T_A = v_1R_{\text{max}}+v_3R_{\text{min}}+ \frac{W}{\mu_{\text{req}}}\sum_{i\in I'_{v_2}}\frac{h_iP_i}{v_1P_{r_A}^{v_1}+v_3P_{r_A}^{v_3}+\sum\limits_{j\in I'_{v_2}-\{i\}} h_jP_j} \tag{27}$$

The first two terms in (27) and (25) are equal, so to determine whether T_A is bigger or lesser than T_B, we only need to consider the last term in each equation. To this end, we divide the last term in (27) by the one in (25), and use $P_{r_A}^{v_1}=\alpha P_{r_B}^{v_1}$ and $P_{r_A}^{v_3}=\alpha P_{r_B}^{v_3}$; thus, after some manipulation, we obtain:

$$\sum_{i\in I'_{v_2}}\frac{\left[v_1P_{r_B}^{v_1}+v_3P_{r_B}^{v_3}\right]h_iP_i}{\left[v_1P_{r_B}^{v_1}+v_3P_{r_B}^{v_3}+h_uP_{\text{u}}\frac{\sum_{j\in I'_{v_2}-\{i\}} h_iP_j}{\sum_{j\in I'_{v_2}} h_jP_j}\right]\sum_{j\in I'_{v_2}} h_jP_j} < \sum_{i\in I'_{v_2}}\frac{h_iP_i}{\sum_{j\in I'_{v_2}} h_jP_j} = \frac{\sum_{i\in I'_{v_2}} h_iP_i}{\sum_{j\in I'_{v_2}} h_jP_j} = 1$$

Thus, $T_A<T_B$. So far, we have shown that there is only one user that is operating at power P_u that is higher than the minimum power required to achieve R_{min}, but we have not shown *which* user is that. It is not difficult to see that T_B in (25) is an increasing function of the received power (i.e., h_uP_u). Hence, the best channel user in $I-\{I_{v_1}\}$ must be chosen to operate at P_u, so the order of that user is v_1+1.

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