

# Scheduling for next generation WLANs: filling the gap between offered and observed data rates

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## Summary

In wireless networks, opportunistic scheduling is used to increase system throughput by exploiting multi-user diversity. Although recent advances have increased physical layer data rates supported in wireless local area networks (WLANs), actual throughput realized are significantly lower due to overhead. Accordingly, the frame aggregation concept is used in next generation WLANs to improve efficiency. However, with frame aggregation, traditional opportunistic schemes are no longer optimal. In this paper, we propose schedulers that take queue and channel conditions into account jointly, to maximize throughput observed at the users for next generation WLANs. We also extend this work to design two schedulers that perform block scheduling for maximizing network throughput over multiple transmission sequences. For these schedulers, which make decisions over long time durations, we model the system using queueing theory and determine users' temporal access proportions according to this model. Through detailed simulations, we show that all our proposed algorithms offer significant throughput improvement, better fairness, and much lower delay compared with traditional opportunistic schedulers, facilitating the practical use of the evolving standard for next generation wireless networks. Copyright © 2009 John Wiley & Sons, Ltd.

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**KEY WORDS:** opportunistic scheduling; resource allocation; wireless LANs; multi-user diversity; wireless MAC; queueing theory

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## 1. Introduction

Wireless access based on 802.11 wireless local area network (WLAN) technology has become increasingly popular and the *de facto* way of connecting to the Internet due to portability and low cost of terminals as well as widespread availability of hot spots. The goal of bringing the data rates of WLAN links close

to wired counterparts has resulted in the workgroup of IEEE 802.11n for specifying the physical layer of next generation WLANs. The draft standard realizes multiple input multiple output (MIMO) technology, which has been shown to improve the quality, reliability, and hence capacity of wireless links significantly, due to the rich scattering environment and spatial diversity provided by multiple antennas at the

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transmitter and receivers [1–4]. Higher capacity links are to be utilized in new backbone networks, such as wireless mesh networks (WMNs), where 802.11-based wireless connectivity is extended to larger coverage areas and aggregate traffic of WLANs is carried over multiple hops of access points. Despite the improved data rates in the physical layer, the actual throughput experienced at the receiver end is much lower due to packet and medium access control (MAC) coordination overhead. In 802.11n, MAC efficiency is enhanced *via* frame aggregation concept [5,6], which reduces the relative percentage of the overhead time by combining multiple MAC layer frames into one physical layer protocol data unit (PPDU). Improving the MAC efficiency increases the throughput of an individual link, however in a multi-user system, the network throughput is determined by transmission scheduling, which includes the order and duration of users' access to the channel. In spite of the advantageous MIMO techniques and aggregation, we have shown that a significant performance gap lies between the available data rates and the throughput provided by channel-dependent scheduling schemes applied at the MAC layer [7].

Opportunistic scheduling algorithms [8–14] have been shown to maximize system capacity by making use of the channel variations. For instance, the main idea in maximum rate scheduling (MRS) [8] is favoring the users that are experiencing the most desirable channel conditions, by riding the peaks. While maximizing capacity, such greedy algorithms may cause unacceptable delays and unfairness. The proportional fair approach [9] mitigates this problem by selecting users according to their relative channel conditions with respect to their own history, resulting in better fairness but lower throughput. In nomadic systems such as WLANs, users are moving slowly, hence their channels are slowly varying, which causes the scheduler to serve the same users repetitively and unserved users to accumulate packets in their queues. Hence another solution is monitoring users' queues and channel states together. In Reference [10], the authors present a scheduling framework, where a generalized utility function is maximized subject to fairness constraints. As for the utility function, the weighted delay-data rate product is considered in Reference [11]. In all of these approaches, scheduled transmissions assume a single packet transmission of constant size, while next generation, 802.11n links involve transmissions of *aggregate* packets of variable size, which can dramatically change the scheduling scenario. A user with a good channel and a long

queue may offer a higher throughput than a user with better channel conditions but shorter queue. Hence, the statement that always selecting the user with the best channel maximizes throughput is not valid anymore. Before any service quality requirements, the utilization of the high data rate links is essential, which requires new scheduling approaches.

The major contribution of this work is the design of scheduling algorithms specifically for the aforementioned new features of next generation WLANs. We introduce a family of scheduling algorithms which involve utility functions/metrics to capture the nature of the transmissions over 802.11n links, so that the offered data rates for high capacity WLANs and WMNs can be provided. In the first part, we present aggregate opportunistic scheduling (AOS), and its two variants, aggregate discrete opportunistic scheduling (ADOS) and proportional aggregate opportunistic scheduling (P-AOS), all of which are based on maximizing the instantaneous throughput considering the queue sizes, physical, and MAC layer parameters. In the second part, we propose predictive block schedulers, in which, the order and duration of transmissions for multiple users are determined with the goal of maximizing the long-term throughput derived the long-term evolution of the queue states. A queuing model is derived for 802.11n aggregate transmissions, and using that model, the average aggregate size is predicted which is then utilized in the design of two schemes, predictive scheduling with time-domain water-filling (P-WF) and predictive scheduling with access guarantees (P-AG).

Another contribution of this work is comprehensive performance analysis of all scheduling algorithms. In the literature, the scheduling algorithms have been evaluated mostly against round-robin scheduling and over different physical interfaces; however, a comparison of those algorithms with each other over the same air interface does not exist. Here, we compare our proposed schemes with the prominent algorithms from the literature [8,9,12–14] considering the same air interface of next generation WLANs. We show that, with the aggregation feature of 802.11n, the classical opportunistic scheduling approaches are no longer optimal. Our AOS algorithms significantly improve the picture, with increased throughput of up to 53% over existing schedulers while permitting relatively fair access. Our block schedulers provide further enhancements at some complexity cost: P-WF algorithm offers the highest throughput and P-AG algorithm promises the best compromise between

throughput and fairness, also offering the lowest delay. Our family of scheduling algorithms provide a set of solutions to compensate for the performance gap between offered rates and observed throughput of existing schedulers so that the effective utilization of next generation WLANs can be facilitated.

The rest of the paper is organized as follows: Section 2 involves a general description of the 802.11n system with physical layer model, capacity calculations, and MAC interface. Section 3 provides an overview of the existing scheduling approaches for wireless networks. Section 4 introduces our proposed family of scheduling algorithms for 802.11n. Section 5 presents performance analysis, and Chapter 6 involves our conclusions with directions for future work.

## 2. System Description

In this paper, we consider the centralized scheduling for the downlink channel, shared by multiple users over 802.11n air interface. The packets destined to different terminals are enqueued separately at the AP as shown in Figure 1, and the scheduler chooses to transmit to one of the terminals based on a scheduling criterion. IEEE 802.11n draft standard specifies major improvements to existing IEEE 802.11a/g WLANs as implementation of MIMO techniques in the OFDM-based physical layer and aggregate frame transmission at the MAC layer. In this section, we review the essentials of physical link level capacity calculation and MAC interface of 802.11n, both of which are later to be used in the scheduling metrics<sup>‡</sup>.

### 2.1. Physical Layer Model and Capacity Calculation

In the physical layer, IEEE 802.11n introduces MIMO in wireless LANs with different antenna configuration modes ( $2 \times 1$ ,  $2 \times 2$ ,  $3 \times 3$ ,  $4 \times 4$ ,  $2 \times 4$ , etc.) along with enhanced coding schemes (e.g., LDPC) [1]. We consider a cell with the AP and mobile terminals equipped with two antennas as shown in Figure 1.

<sup>‡</sup>The capacity calculations consider the MIMO-based air interface of 802.11n given in Reference [1], which was one of the strong candidates at the time of this work. The schedulers proposed in this paper assume the physical and MAC layer specifications given in Reference [1], but all the principles can be similarly applied by only adapting some parameters (if necessary) to reflect the modifications of the later versions of this standard.

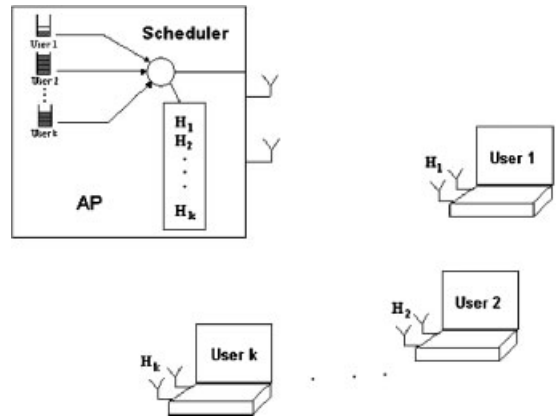


Fig. 1. A typical 802.11n AP and terminals.

The system is a closed-loop MIMO OFDM system in which the mobile users measure and send their channel states as feedback to the AP. Each MIMO wireless channel is represented *via* the channel matrix  $\mathbf{H}_i$ , modeling large-scale path loss, shadowing and small-scale multi-path fading effects for user  $i$ . In this model, since the fading characteristics between individual antenna pairs are spatially correlated, the non-line-of-sight terms of the channel matrices are formed by the multiplication of a matrix with independent identically distributed complex Gaussian random variable elements with transmit and receive correlation matrices. We assumed that the feedback channel, hence channel information is error-free, which is possible through strong error correction. Also, due to low speeds of WLAN users, the coherence time can be safely assumed to be large enough for slow fading, so that the channel matrix remains stationary during a transmission opportunity.

In OFDM-based systems, the channel capacity is calculated by partitioning the system into multiple subchannels that correspond to different subcarriers. Assuming equal number of transmit and receive antennas,  $M$ , the capacity formula for MIMO OFDM system is given as [15]

$$C_i = \frac{B}{N} \sum_{k=0}^{N-1} \log_2 \left( \det \left( \mathbf{I}_{MN} + \rho \mathbf{H}_i \left( e^{j2\pi \frac{k}{N}} \right) \mathbf{H}_i^H \left( e^{j2\pi \frac{k}{N}} \right) \right) \right)$$

$$\text{with } \mathbf{H}_i \left( e^{j2\pi \theta} \right) = \sum_{l=0}^{L-1} \mathbf{H}_{i,l} e^{-j2\pi l \theta} \quad (1)$$

where  $N$  is the number of OFDM subcarriers,  $L$  the number of resolvable paths, and  $\mathbf{H}_{i,l}$  represents the  $l$ th tap of the discrete-time MIMO fading channel

impulse response for user  $I$  [15]. The channel matrix is an expanded version of the  $M \times M$  by size  $NM \times NM$  with the original MIMO channel matrices over the diagonal axis and zero otherwise, i.e.,  $\mathbf{H}_i = \text{diag} \{ \mathbf{H}_i (e^{j2\pi(k/n)}) \}_{k=0}^{N-1}$ . Capacity figures reflect maximum transmission rate based on the channel state.

For our system model, the number of antennas ( $M$ ) is set as two. The actual 802.11n system is a multi-rate system with discrete data rates assigned from the set  $\{24, 36, 48, 72, 96, 108, 144, 192, 216\}$  Mbps. The rate matching mechanism is employed at the sender node (which is AP for downlink traffic) based on the channel conditions, as specified in Reference [1].

## 2.2. MAC Interface

IEEE 802.11n next generation WLANs employ enhanced distributed channel access (EDCA), which can be viewed as an enhancement on the basic distributed coordination function (DCF) of IEEE 802.11 and they are envisioned to support the multimedia extensions specified in IEEE 802.11e [16]. EDCA enhances the original DCF to provide prioritized QoS. Four access categories—background, best effort, video, and voice—are defined, and traffic from different categories are assigned different inter-frame spaces and contention window parameters. For ease of exposition, in this work, we consider the case with a single access category. With a single access category, contention channel is similar to DCF, however, our model and analysis can be extended to the case of multiple access categories. Despite the improved data rates in the physical layer, the actual throughput levels experienced at the MAC layer are much lower due to several sources of overhead. Deferral and back off times in random access and collisions cause access delays, which can be much larger than frame transmission delays that are especially small with high physical layer data rates provided by MIMO. Access coordination can be performed by control packets (RTS/CTS) so that probability of collisions and delay for recovery are reduced at some additional overhead cost. Even though the lengths of control packets are much shorter than data packets, the time wasted due to control packet transmission is not negligible [5] due to much lower transmission rate. Another factor that contributes to reduction in throughput is the physical layer convergence protocol (PLCP) overhead that is added to all packets for channel estimation. In order to reduce the relative percentage of the time loss due to all

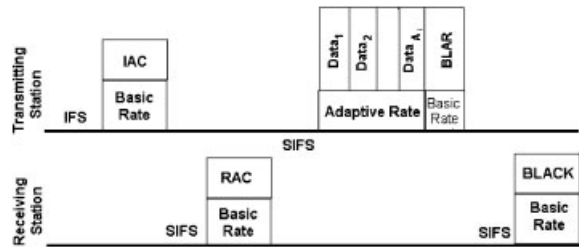


Fig. 2. Example aggregate frame transmission.

sources of overhead, the method of frame aggregation has been included in the IEEE 802.11n specification. With this feature, once access is gained by a station or AP, multiple MAC layer protocol data units (MPDUs) are combined and transmitted in one PPDU. The total duration of time the sender owns the channel is named as a transmission opportunity (TXOP).

Figure 2 shows a TXOP including the two-way handshake with frame aggregation as specified in 802.11n [1]. Initiator aggregate control (IAC) and responder aggregate control (RAC) are RTS/CTS-like reservation messages, which also involve training sequences to assist MIMO channel estimation and data rate selection. After IAC/RAC exchange, the aggregate frame is transmitted and an acknowledgement is requested *via* the block ACK request (BLAR) packet. The destination station replies with a block ACK (BLACK) packet, first introduced in IEEE 802.11e that contains the reception status of packets in the aggregation. The data packets are transmitted at the selected transmission rate according to the quality of the channel, while the control packets are transmitted at the basic rate. Without loss of generality, we assume one of the access categories where the initial interframe space is equal to DIFS, and the other inter frame spacing values are set similarly as in the 802.11n specification [1]. All the packets in the aggregate are destined to the same station. The maximum number of packets that can be included in the aggregate is bounded and the limit is a configurable parameter, as specified in Reference [1]. Aggregation feature has been specified for both uplink and downlink transmissions. However, here, since only the downlink scheduling is considered, the only traffic source is the AP.

## 3. Related Work

In this section, we provide an overview of prominent scheduling algorithms in the literature, considering the

downlink scheduling algorithms to be implemented at the AP. The IEEE 802.11n standard [1] lists the *longest queue* (LQ) algorithm, as the default scheduling scheme, where the scheduler simply selects the station with the largest number of packets in its queue. In other words, the selected user  $k_i^*$  in the  $i$ th TXOP is found as  $k_i^* = \arg \max_k Q_i^k$ , with  $Q_i^k$  being the number of packets destined to the  $k$ th user in the  $i$ th TXOP. The reasoning behind the LQ algorithm is to maximize the aggregate size for maximizing the throughput, with the basic assumption that users are experiencing similar channels with equal data rates. However, the channel quality of stations can vary notably due to time-varying wireless channel and mobility [17].

Scheduling transmissions by exploiting the channel's fluctuations and multi-user diversity, and assigning access to the stations according to their channel quality is known, in general, as opportunistic scheduling [8–14]. In MRS [8], the quality metric for decision is information theoretical channel capacity. At each TXOP  $i$ , the selected user  $k_i^*$  is obtained as  $k_i^* = \arg \max_k C_i^k$ , where  $C_i^k$  denotes the instantaneous capacity calculated for the  $k$ th user in the  $i$ th transmission opportunity. For 802.11n, due to MIMO operation, spatial diversity is obtained, so that the capacities of individual channels are enhanced as calculated in Equation (1), and with multi-user diversity and MRS, the overall system capacity is maximized since the transmission is granted to the user achieving the highest capacity. Despite maximizing the system capacity, MRS algorithm may result in unfairness in a network setting. *Proportional fair queuing* (PFQ) alleviates this problem with an alternative approach by favoring users according to the relative change in channel capacity [9]. In PFQ, the selected user,  $k_i^*$  of the  $i$ th TXOP is determined as  $k_i^* = \arg \max_k (C_i^k / \bar{C}_i^k)$ , where  $\bar{C}_i^k$  denotes the average channel capacity of the  $k$ th user until the  $i$ th transmission opportunity. PFQ has found practical applications and an implementation has been standardized for cellular IS-856 system, which is also known as HDR [9].

When the above opportunistic schemes are employed, users with high capacity links tend to have small queues, while users subject to poor channel conditions suffer from queue overflows and long delays. In Reference [12], an opportunistic scheme that stabilizes the network for all arrival rate vectors within the stability region of the network is applied. The policy uses a queue-weighted rate metric and

in this downlink setting tries to select user  $k_i^*$  as  $k_i^* = \arg \max_k C_i^k Q_i^k$ . The inclusion of queue length in this scheme provides important insights for fairness. For instance, assume initially that the queue sizes are similar for all users, except for one user whose channel is superior to others. The user with the best channel will be selected and served so its queue size will be reduced; however, in the next scheduling instant, the advantage of better channel quality will be alleviated by the smaller queue size, yielding transmission to other users. We refer to this scheduler as *capacity queue scheduler* (CQS) throughout this paper. Another scheme that considers the user queues together with data rates is *shortest remaining processing time first* (SRPT) method [13], where the scheduling metric is defined as the amount of time it takes to serve all the packets of a given queue. The scheduler tries to choose the user,  $k_i^*$ , whose queue can be drained in the shortest amount of time, i.e.,  $k_i^* = \arg \min_k (Q_i^k / C_i^k)$ .

In all of these approaches, scheduled transmissions assume a constant packet/frame size and the scheduler operates at the physical layer, considering the channel quality and/or queue level for the decision of the selected user. Once the user is selected, the implicit assumption is that a single physical layer data unit is transmitted directly, without any overhead, hence the link is fully utilized. The only existing scheduling scheme that considers aggregation is *opportunistic auto rate* (OAR) protocol, where users are served in a round-robin fashion, and the users with better channel conditions are allowed to transmit with larger aggregate sizes [14]. The number of packets transmitted for a user depends on the ratio of the user's data rate to basic rate of 802.11. OAR algorithm provides throughput and temporal fairness, since the packet transmission times for each user are made equal.

With the aggregation feature, the advantages of MRS and the statement that selecting the user with the highest channel capacity maximizes the throughput is not valid anymore. In other words, a user with a fair channel and long queue may offer a much higher throughput than a user with a good channel but small queue size. Algorithms such as SRPT favors users with high capacity and small queue sizes, which is not suitable with systems implementing frame aggregation, since small aggregate sizes cause low throughput. OAR considers frame aggregation and provides temporal fairness, but does not aim throughput maximization. The behavior of PFQ, CQS, and LQ algorithms with frame aggregation needs to

be investigated. In this work, we study all of the aforementioned algorithms with frame aggregation in the setting of next generation IEEE 802.11n WLANs, and we propose new scheduling algorithms that jointly consider channel and queue states of users through the calculation of observed throughput at the user level.

#### 4. Scheduling Algorithms for Next Generation WLANs

Our proposed scheduling algorithms are presented in two parts, (1) AOS that selects a user for each transmission opportunity while maximizing the instantaneous network throughput, and (2) Predictive block scheduling that provides schedules, i.e. transmission duration and order of multiple users, so as to maximize the overall throughput in the long term.

##### 4.1. Aggregate Opportunistic Scheduling

Despite the performance enhancing techniques introduced by IEEE 802.11n, namely MIMO and frame aggregation, the throughput observed by the system depends on the channel and queue states of the selected user, hence scheduling. Our motivation here is that throughput can essentially shape scheduling as scheduling shapes performance and we propose AOS algorithm, where the scheduler tries to maximize the instantaneous throughput when the AP is transmitting a number of packets in aggregate to a selected user. In other words, for  $i$ th TXOP, the AOS scheduler selects a user  $k_i^*$  as

$$k_i^* = \arg \max_k S_i^k \quad (2)$$

where  $S_i^k$  is the throughput calculated for  $i$ th TXOP and  $k$ th user with the actual system overhead and parameters, as shown next. Considering downlink traffic destined to the  $k$ th station in the  $i$ th TXOP and given that there are no collisions, losses are merely due to protocol, packet, and physical layer overhead, resulting in instantaneous downlink throughput which is calculated as

$$S_i^k = \frac{A_i^k \cdot L_P}{L_{IAC}/r_0 + L_{RAC}/r_0 + 4 \cdot T_{PLCP} + DIFS + 4 \cdot \tau + 3 \cdot SIFS + L_{BLACK}/r_0 + L_{BLAR}/r_0 + A_i^k \cdot (L_P + L_{MH})/C_i^k} \quad (3)$$

with  $A_i^k$  being the instantaneous aggregate size to user  $k$  at  $i$ th TXOP and  $L_P, L_{IAC}, L_{RAC}, L_{BLACK}, L_{BLAR}$  are the length of the data, reservation, ACK, and ACK request packets, respectively.  $L_{MH}$  is the MAC header in bits,  $T_{PLCP}$  the duration of physical layer training header,  $\tau$  the one-way propagation delay and DIFS, SIFS are inter-frame spacing times specified in 802.11n [1]. Finally,  $r_0$  is the basic data rate at which control packets are transmitted and  $C_i^k$  is the instantaneous capacity, i.e., maximum achievable data rate to communicate with user  $k$ , which depends on the channel state as calculated in Equation (1). Instantaneous aggregate size is determined as the minimum of the user's queue size and the maximum allowable aggregate size, which is set according to limit of transmission opportunity duration. The selection metric in Equation (3) considers both channel and queue states, similar to [12], but now taking into account the effects of frame aggregation in a realistic manner, rather than a weighted sum.

Two versions of AOS are also developed with slight modifications. In *ADOS*, again the throughput maximizing user is selected, but the throughput values are calculated by substituting one of the specified transmission rates of 802.11n,  $r_i^k$  for capacity,  $C_i^k$  in throughput calculation in Equation (3).  $r_i^k$  is selected from the set,  $R_d = \{12, 24, 36, 48, 72, 96, 108, 144, 192, 216\}$  Mbps through a rate matching mechanism, as defined in Reference [1]. In *P-AOS*, we propose to apply PFQ approach to AOS to provide fairness. Instead of favoring the user that maximizes the instantaneous throughput, the user with the largest change in throughput is selected at the  $i$ th transmission opportunity. In other words, the selected user  $k_i^*$  is found as

$$k_i^* = \arg \max_k \frac{S_i^k}{\overline{S_i^k}} \quad (4)$$

where  $\overline{S_i^k}$  denotes the average throughput for the  $k$ th user until  $i$ th transmission opportunity. The main difference between the *P-AOS* algorithm and the PFQ algorithm is that the PFQ algorithm performs scheduling decisions according to channel variations only, whereas *P-AOS* tracks variations in queue size as well. The proposed AOS, *ADOS*, and *P-AOS* algorithms provide a good compromise between channel and queue states for

improving system's actual throughput. The scheduling decisions consider per user queue and aggregate size, per user channel data rates and overhead values, all of which are already available at the AP.

## 4.2. Predictive Block Scheduling

Selecting the user that maximizes the instantaneous throughput at a specific transmission opportunity may lower the throughput in the subsequent transmission opportunities. Likewise, increasing the participation of low-capacity users can later enable the higher capacity users to transmit with larger aggregate sizes and hence result in higher efficiency and throughput. Our aim in this section is to design *block scheduling* algorithms that perform allocation of multiple users, so as to maximize the overall throughput over a long term, the duration of which is set as an external parameter. We propose *predictive block scheduling*, where the access privileges and proportions of users are determined based on *predicted* per user aggregate size and throughput values. These predicted values are further utilized in determining the transmission sequence and the associated aggregate sizes to be used for scheduled users. A queuing model is first developed for packet transmissions with frame aggregation in 802.11n downlink channel and then the outcomes of the queuing model, namely long-term average aggregate size and average throughput are utilized in designing the heuristics of two block schedulers, namely *P-WF* [18] and *P-AG*. Later on, we demonstrate that maximization of long-term throughput enhance the performance further.

### 4.2.1. Queuing formulation

In this section, we devise a queuing model for aggregate frame transmissions of the 802.11n MAC by extending the bulk service model in Reference [19]. From this queuing model, we compute the state probabilities, where each state corresponds to the number of packets included in the bulk that is an aggregate frame. By using the obtained state probabilities, we compute the expected aggregate size and throughput per user, and then the long term overall system throughput and accordingly design the metrics of the block schedulers. Figure 3 shows the bulk service model, where the packets are served collectively in groups and incoming packets are enqueued. Packets arrive one by one with an average rate,  $\lambda$  packets/s. All of the packets in the queue are served together if the number of packets is less than the bulk size,  $L$ . If the queue length exceeds

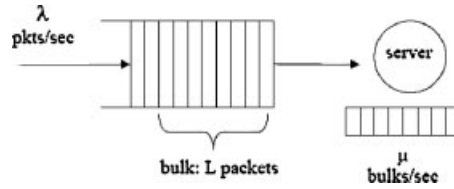


Fig. 3. Bulk service system.

$L$ , only the first  $L$  packets are served. The bulk service rate,  $\mu$ , is defined as the rate of serving bulks, which is assumed constant for all states [19].

The assumption of constant bulk service rate implies that the processing rate in bits per second is to be increased proportionally with the bulk size. For transmissions over a wireless link, the channel data rate can vary due to variations in channel conditions, but in a given rate setting data transmission rate does not change with bulk size. Moreover, in realistic aggregate frame transmissions MAC and physical layer overhead should also be taken into account in determining the service rates. Therefore, for our queuing model of aggregate transmission, the service rate  $\mu_j$  is variable and is obtained as

$$\mu_j = \begin{cases} \frac{\mu}{j} \cdot \left( \frac{j \cdot L \cdot P}{j \cdot (L \cdot P + L_{\text{MH}}) + L_{\text{overhead}} + r \cdot T_{\text{IFS}}} \right) & 1 \leq j < L, \\ \frac{\mu}{L} \cdot \left( \frac{L \cdot L \cdot P}{L \cdot (L \cdot P + L_{\text{MH}}) + L_{\text{overhead}} + r \cdot T_{\text{IFS}}} \right) & j \geq L, \end{cases} \quad \text{bulks/s} \quad (5)$$

where  $j$  is the number of packets involved in the aggregate,  $\mu$  the rate of serving bulks,  $L_{\text{overhead}}$  accounts for the total overhead including PHY and MAC headers,  $T_{\text{IFS}}$  the sum of interframe durations,  $r$  the channel data rate determined according to the channel conditions which vary over time due to fading.

Assuming Poisson packet arrivals, i.e., exponential inter arrival times, helps us to model the queuing system in terms of a Markov chain, due to the memoryless property of exponential distribution [19]. Although Poisson distribution may not exactly model arrival patterns of current applications, it provides an adequate reference for comparing the evolution of different user queues in the AP, hence a relative performance can be obtained for scheduling purposes. Similar assumptions have been made in previous work on modeling WLAN traffic [20], aggregate load in WMNs [21], as well as scheduler design papers [22]. Figure 4 depicts the Markov chain representation of the queuing model of aggregate frame transmissions, defining the state as the number of packets in the queue. Packets arrive at average rate  $\lambda$ , and bulks are served at rate  $\mu_j$ , given by Equation (2). Using this model, we derive the state

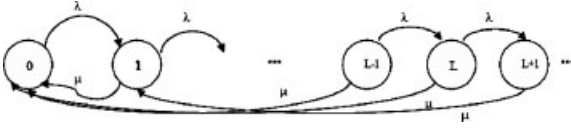


Fig. 4. Markov-chain representation of aggregate frame transmission.

probabilities,  $p_1, p_2, \dots, p_L$ , at steady state by solving the balance equations

$$\lambda p_0 = \mu_1 p_1 + \mu_2 p_2 + \dots + \mu_L p_L \Rightarrow$$

$$p_0 = \left(\frac{1}{\lambda}\right) \sum_{j=1}^L \mu_j p_j \quad (6a)$$

$$(\lambda + \mu_j) p_j = \mu_L p_{j+L} + \lambda p_{j-1} \quad 1 \leq j \leq L \quad (6b)$$

$$(\lambda + \mu_L) p_j = \mu_L p_{j+L} + \lambda p_{j-1} \quad j \geq L \quad (6c)$$

Converting the balance equations into the alternative form by taking the  $z$ -transform<sup>§</sup>, we obtain  $P(z)$  in rational form as follows:

$$P(z) = \frac{\sum_{j=1}^L [z^{L+j} (\mu_j - \mu_L) - z^L (\mu_j + \mu_L \mu_j / \lambda) + \mu_L z^j + \mu_L \mu_j / \lambda] p_j}{\lambda z^{L+1} - (\lambda + \mu_L) z^L + \mu_L}, \text{ i.e.,}$$

$$P(z) = \frac{N(z)}{D(z)} \quad (7)$$

The global sum of probabilities should be equal to 1, requiring  $P(1) = 1$  to be satisfied. Since both  $N(1) = 0$  and  $D(1) = 0$ , we need to utilize the L'Hospital rule and solve  $\lim_{z \rightarrow 1} N'(z)/D'(z) = 1$ . The next step is to obtain state probabilities by taking the inverse transform of  $P(z)$ . The fact that the bulk service rates are state-dependent has caused the order of  $N(z)$  to be greater than the order of  $D(z)$ , so  $P(z)$  cannot be simplified. We take an alternative approach as follows: similar to the bulk service model solution in Reference [19], out of the  $(L+1)$  roots of  $D(z)$ ,  $(L-1)$  roots are located within the unit circle. Due to the fact that the  $z$ -transform of a probability distribution is analytical inside the unit circle,  $P(z)$  should be bounded, which implies that  $(L-1)$  zeros of  $P(z)$  must also be the

roots of the numerator  $N(z)$ .  $N(z)$  must also vanish at each of the  $(L-1)$  roots of  $D(z)$  inside the unit circle. This constraint results in a set of  $(L-1)$  equations. Including the equation provided by the L'Hospital rule, we obtain  $L$  equations for probabilities  $p_1, p_2, \dots, p_L$ , and Equation (5) provides the solution for  $p_0$ . The set of equations is solved *via* numerical computations, obtaining the steady-state probabilities of the system for all the states up to the aggregate limit  $L$ . The expected aggregate size,  $\bar{A}$ , and expected throughput,  $\bar{S}$ , are found as the ensemble average, *via*

$$\bar{A} = \sum_{j=1}^L j \cdot p_j + L \cdot \left(1 - \sum_{j=0}^L p_j\right) \quad (8)$$

$$\bar{S} = \sum_{j=0}^L p_j S(A_j) + (1 - \sum_{j=0}^L p_j) S(L) \quad (9)$$

where  $S(A_j)$  is the throughput achieved with aggregate size  $A_j$ .

The queuing model provides us the *expected aggregate size* and *expected throughput* for a single queue (user) given the service rate and applied load. Considering the multi-user scenario with time-division

multiplexed traffic, the parameters for the queuing model need to be modified by taking the temporal access proportions into account. Given the temporal access proportion of a user as  $\pi_n$ , where  $\pi_n \in [0,1]$ , the effective channel service rate of that user is to be computed by scaling its link rate by  $\pi_n$ . From Equation (7), it can be verified that scaling the service rate by  $\pi_n$  with a given load level has the same effect as keeping service rate and scaling the load level by a factor of  $1/\pi_n$ . Hence, the effective load at the  $n$ th user queue is obtained as  $\lambda_n/\pi_n$ , and the bulk service rate  $\mu_j$  is found from Equation (5) as a function of the data rate of the served user's wireless channel ( $r_n$ ) and the aggregate size  $j_n$ . After computing the state probabilities, the expected throughput per user  $n, \bar{S}_n$ , is obtained as

$$\bar{S}_n = f(\pi_n) = \begin{cases} \frac{\lambda_n}{\pi_n}, & \frac{\lambda_n}{\pi_n} < S(L) \\ S(L), & \frac{\lambda_n}{\pi_n} > S(L) \end{cases} \quad (10)$$

<sup>§</sup>The  $z$ -transform of  $p$  is defined as  $P(z) = \sum_{j=1}^{\infty} z^j p_j$ .



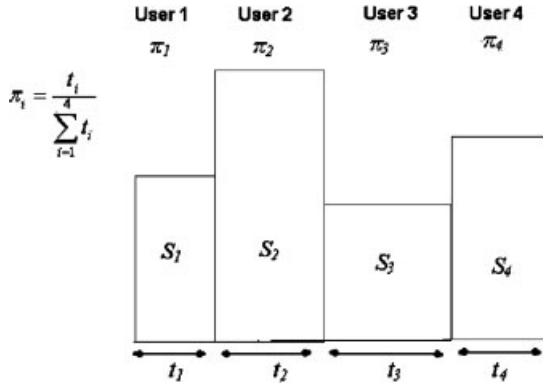


Fig. 5. Channel access and temporal proportions.

where  $S(L)$  is the maximum throughput that can be achieved with the maximum allowed aggregate size,  $L$ . The overall network throughput is obtained as the weighted average of the per user throughput values:

$$S_{\text{total}} = \sum_{n=1}^N \pi_n \bar{S}_n \quad (11)$$

with  $N$  being the total number of users to be scheduled. Figure 5 depicts an illustration of the transmission durations, temporal access proportions, and observed throughput per user with  $N=4$ .

The calculation of the state probabilities and estimation of queue size and throughput are to be implemented the AP. The AP has the per user information of traffic load, channel (service) rates and queue states available. Channel states are assumed to be stationary within a scheduling duration, as fading is assumed to be slow due to low mobility in indoor WLANs.

#### 4.2.2. Predictive scheduling with time water-filling

In order to maximize the total throughput,  $S_{\text{total}}$  obtained in Equation (11), we propose *predictive scheduling with time-domain water-filling* (P-WF) as a block scheduling solution that optimizes temporal access proportions,  $\pi_n$  for a given number of users,  $N$ . The scheduling problem is described as

$$\arg \max_{\pi_n} \sum_{n=1}^N \pi_n \bar{S}_n \text{ such that } \sum_{n=1}^N \pi_n = 1 \quad (12)$$

The above problem resembles the power allocation problem among users or multiple transmit antennas for maximizing capacity of multi-user or multi-antenna fading channels, solved by water-filling. In a water-filling problem, in general, the aim is to maximize the weighted average of a quantity in the form

$$\max \sum_{n=1}^N (\beta + \gamma_n x_n) \text{ with the constraint } \sum_{n=1}^N x_n = 1 \quad (13)$$

The solution for  $(x_1, x_2, \dots, x_N)$  is given as [23]

$$x_n^{\text{opt}} = \left( \zeta - \frac{\beta}{\gamma_n} \right)_+, \quad n = 1, \dots, N \quad (14)$$

where  $(\theta)_+$  denotes  $\max(\theta, 0)$ . For the power allocation problem, the solution,  $x_n^{\text{opt}}$  is the optimal transmission power level for each channel  $n$  with SNR value  $\gamma_n$  and the power cut-off value,  $\zeta$  is a function of receiver's acceptable threshold SNR. We exploit the mathematical analogy between Equations (12) and (13), where power level is analogous to temporal access proportion. Then, we apply the concept of waterfilling for determining the time proportions  $\pi_n$  that maximize  $S_{\text{total}}$ , and we name this method as *time-domain water-filling*. In order to achieve a full analogy between the equation pairs, we add a constant into the summation term on the left in Equation (11) and obtain

$$S' = \sum_{n=1}^N (\beta + \pi_n \bar{S}_n) \quad (15)$$

Maximizing  $S'$  is equivalent to maximizing  $S_{\text{total}}$ , so the waterfilling solution is found as

$$\pi_n = \left( \zeta - \frac{\beta}{\bar{S}_n} \right)_+, \quad n = 1, \dots, N \quad (16)$$

Unlike traditional waterfilling, the solution cannot be computed directly due to the coupling between the waterfilling terms,  $\bar{S}_n$  and  $\pi_n$ . At this point, we propose the following heuristic algorithm to find best  $\pi_n$  values:

1. Initialize all temporal proportions equally, as  $\pi_n^0 = 1/N$  for  $n = 1, \dots, N$ .
2. For iteration  $i$ 
  - Compute the effective load values,  $\lambda_n^i = \lambda_n^0 / \pi_n^i$ , for each user,  $\forall n$ .

- Calculate the per user average aggeragate size,  $A^i(\lambda_n^i)$  and per user throughput,  $S^i(\lambda_n^i)$  from the analytical model.
- Find access proportions from waterfilling solution as  $\pi_n^{i+1} = (\zeta - (\beta/S^i(\lambda_n^i)))_+$  also solving for cut off value,  $\zeta$  using  $\sum_{i=0}^N (\zeta - (\beta/S^i(\lambda_n^i)))_+ = 1$ . Initially, all of the access proportions are assumed to be greater than 0, and cut off is obtained as  $\zeta = 1/N + 1/N \sum_{i=0}^N (\beta/S^i(\lambda_n^i))$ . If  $\beta/S^i(\lambda_n^i) > \zeta$  is satisfied for all users, the iteration is completed. Otherwise, cutoff is calculated by eliminating users with low throughput, until the number of users surpassing  $\zeta$  is consistent with the number of terms in the summation.

Step 2 with its substeps is repeated until, after a finite number of iterations, the access proportions ( $\pi_n$ s) converge. The resulting proportions indicate optimal transmission durations of the users relative to the total transmission sequence in which scheduling is applied. Users below the threshold ratio are not served, similar to waterfilling schemes for power allocation, where poor channels are not allowed to transmit when their signal to noise ratio (SNR) fall below the cutoff value.

Having determined the temporal access proportions, next, we need to determine the sequence of transmissions for the selected active users. For this purpose, we use an approach that is similar to calculation of finish tags in fluid fair queuing [24]. Each active user is assigned a turn number, which indicates the number of times the user will be given access throughout the total scheduling duration. The turn number,  $t_n$  for user  $n$  is determined in two steps: first, the ratio of the access proportion of the user to the transmission duration of serving that user once is calculated, then all calculated turn numbers are scaled with respect to the minimum turn number. In other words

$$t_n = \frac{\pi_n^*}{T_n} = \frac{\pi_n^*}{((\overline{A_n} \cdot L_p) / r_n + T_{\text{overhead}})} \quad (17)$$

$$t' = \min_{\pi_n^* > 0} \left( \frac{\pi_1^*}{T_1}, \frac{\pi_2^*}{T_2}, \dots, \frac{\pi_{N_{\text{Active}}}^*}{T_{N_{\text{Active}}}} \right),$$

$$t_1 = \frac{t_1}{t'}, t_2 = \frac{t_2}{t'}, \dots, t_{N_{\text{Active}}} = \frac{t_{N_{\text{Active}}}}{t'} \quad (18)$$

where  $T_n$  is the transmission duration of serving user  $n$ ,  $\overline{A_n}$  is the average aggeragate size calculated from the

queuing model for user  $n$ ,  $T_{\text{overhead}}$  refers to the sum of all the overhead terms in Equation (1). The optimal solution can yield some of the users with a zero access proportion, so  $N_{\text{active}}$  is the total number of users with a non-zero access proportion. The transmissions of the active users are scheduled in ascending order of their turn numbers, which makes sure that the users with the smaller access proportions get their allocation before the others.

### 4.2.3. Predictive scheduling with access guarantees

In this section, we propose a second heuristic algorithm to perform block scheduling that provides access guarantees to all users. The goal is again to maximize the throughput and find the solution for temporal access proportions,  $\overline{\pi} = (\pi_1, \pi_2, \dots, \pi_N)$  in the problem in Equation (11), this time making sure that each user gets a share. For this purpose, we propose a search algorithm that alters the temporal proportion values,  $\overline{\pi} = (\pi_1, \pi_2, \dots, \pi_N)$  and computes  $S_{\text{total}}$  until it is maximized. We propose an iterative heuristic for performing this search as follows:

- (1) Initialize access proportions in an opportunistic manner in accordance with users' channel data rates ( $r_n$ ) as

$$\pi_n^0 = \frac{r_n}{\sum_{i=1}^N r_n} \quad n = 1, \dots, N \quad (19)$$

- (2) For iteration  $i$ , update  $\pi_n^i$  as

$$\pi_n^i = \left( \pi_n^0 \right)^{\alpha_i}, \quad \forall n \quad n = 1, \dots, N \quad (20)$$

where  $\alpha_i$  is a tuning parameter for the  $i$ th iteration. Since the summation of the temporal proportions of all users should be equal to unity, the proportions should be normalized so that

$$\pi_n^i = \frac{\pi_n^i}{Q}, \quad \forall n$$

$$\sum_{n=1}^N \pi_n^i = Q \quad (21)$$

With the given value of  $\pi_n^i$ :

- Compute the effective load values,  $\lambda_n^i = \lambda_n^0 / \pi_n^i$ , for each user,  $\forall n$ .
  - Calculate the average aggregate size,  $A^i(\lambda_n^i)$  and throughput,  $S^i(\lambda_n^i)$  from the analytical model for all users, by considering their individual data rates.
  - Compute the total throughput for the  $i$ th iteration as  $S_{\text{total}}^i = \sum_{n=1}^N \pi_n^i S_n^i$ , and record.
- (3) Repeat step 2 by varying  $\alpha_i$  in each iteration, until  $\alpha$  and access proportions remain unchanged, which occurs when the maximum throughput is achieved. As discussed below, the throughput first increases as  $\alpha$  is increased, but then starts to decrease, revealing the maximizing value. For the determined value of  $\alpha^*$ , the temporal access proportions and aggregate sizes are determined of each user.

$$\max_{\alpha_i} S_{\text{total}}^i \Rightarrow \begin{cases} \bar{\pi}^* = [\pi_1^*, \pi_2^*, \dots, \pi_N^*] \\ \bar{A}^* = [A_1^*, A_2^*, \dots, A_N^*] \end{cases} \quad (22)$$

It is worthwhile to note that the exponent  $\alpha$  signifies the degree of opportunism, which is the trade off between throughput and fairness. For small values of  $\alpha$ , the algorithm behaves like the LQ algorithm, yielding for users with larger queues, while for large  $\alpha$ , the algorithm converges to the MRS algorithm, where users with high data rates are served with high access proportions. The best value  $\alpha^*$  that is obtained at the end of the iterations, results in a behavior in between these two extreme cases, leading up to the temporal access proportions for maximizing throughput while providing access guarantees for all users. The value for  $\alpha^*$  depends on network scenario, i.e., the load and distribution of user data rates. At low load, the optimal  $\alpha_i$  obtained is relatively low, so that the aggregate sizes for high-quality stations can be kept large to provide satisfactory throughput values, which can be done by reducing the access proportion. On the other hand, as the load is increased, the stations can transmit with large aggregate sizes without needing to decrease their access proportion, so  $\alpha_i$  is increased. The best value of  $\alpha_i$  gives the throughput maximizing temporal access proportion, providing an opportunity for all users. Given the access proportions, the turn numbers are calculated using Equations (17) and (18), and transmissions are scheduled

in ascending turn numbers, similar to the P-WF scheme.

Both block scheduling algorithms offer temporal shares of access, in addition to scheduling order, with allocations that provide maximized long-term throughput while at the same time providing better fairness and access guarantees in P-AG. Access guarantees within a block results in finite delay for head-of-line packets of queues. However, we cannot offer QoS guarantees when the load is not supportable for all queues in the network, in which case the system is out of the stability region.

## 5. Performance Evaluation

In this section, the performance of proposed *AOS* (*ADOS*, *P-AOS*) and *predictive block scheduling* (*P-WF* and *P-AG*) schemes are evaluated in comparison to the scheduling disciplines from the literature namely LQ [1], MRS [8], PFQ [9], CQS [12], SRPT [13], and OAR [14]<sup>||</sup>. The simulations are carried out in the OPNET simulation environment, modeling the wireless channel, physical layer parameters, 802.11 MAC layer with 802.11n enhancements and the scheduling algorithms. For the wireless channel, the log-normal path loss model is simulated with path loss exponent of 2 and log-normal shadowing deviation of 3 dB within a distance of 5 m from the transmitter, and path loss exponent of 3.5 and shadowing variation of 5 dB for distances larger than 5 m. As for fading, the Channel B model developed for small office environments and non line-of-sight conditions by TGnSync group is implemented with an rms delay spread of 15 ns. Doppler frequency is 5 Hz, which allows slow fading, so that the channel remains static during a transmission opportunity. In the physical layer, a practical,  $2 \times 2$  MIMO configuration is assumed. OFDM parameters, such as guard interval, number of subcarriers, etc., are chosen according to the 802.11n specifications in Reference [1]. Further details of the MIMO channel can be found in Reference [25]. IEEE 802.11n data rates are adaptively selected for each user, from the set {24, 36, 48, 72, 96, 108, 144, 192, 216} Mbps according to the instantaneous channel

<sup>||</sup>The OAR algorithm defines the aggregate size as the ratio of the data rate of the station over basic rate. Here, we have considered two versions of OAR, where the algorithm is applied with a basic rate of 12 Mbps (OAR-12) and with a basic rate of 24 Mbps (OAR-24).

Table I. Some MAC-related parameters.

Parameter	Value
SIFS	$16 \mu s = 16 \times 10^{-6} s$
DIFS	$34 \mu s = 34 \times 10^{-6} s$
PLCP overhead	$44.8 \mu s = 448 \times 10^{-7} s$
$T_{IAC}$	$11.2 \mu s = 112 \times 10^{-7} s$
$T_{RAC}$	$8.7 \mu s = 87 \times 10^{-7} s$
$T_{BLACK}$	$48.7 \mu s = 487 \times 10^{-7} s$
$T_{BLAR}$	$9 \mu s = 90 \times 10^{-7} s$

conditions as explained in References [1,24]. The basic rate, i.e. the common rate for control packet transmission is selected as 24 Mbps. Finally, some of the MAC related parameters of the simulation model are given in Table I. The maximum number of packets allowed in frame aggregation,  $L$ , is assumed as 63. The downlink traffic is modeled by fixed size (1024 bytes) packets that arrive due to the Poisson distribution with varying arrival rates. Similar load level is assumed for each station, which is increased until the network is brought to saturation. Random topologies are simulated with an AP in the middle and 12 stations uniformly distributed within a radius of 25 m. Each network topology is a multi-rate scenario, where the data rates of users are assigned *via* rate matching based on their locations and fading channel conditions.

In Reference [7], we have studied the effect of aggregation on scheduling by comparing the throughput of three existing scheduling algorithms MRS, PFQ, and LQ over 802.11n air interface. We have shown that, without frame aggregation, MRS shows the best performance, however, when frame aggregation is applied, the performance is reversed and the LQ scheme achieves the highest throughput. This is because of the fact that in MRS, the users with better channel capacities are served frequently so their queues do not fill up, resulting in small aggregate size and low throughput, while the simplest queue aware scheduling scheme, LQ leverages the advantage of frame aggregation. These results motivated us for designing jointly queue and channel aware schedulers for the given 802.11n air interface.

In the following, we provide the performance analysis considering our proposed schedulers AOS, ADOS, P-AOS, P-WF, and P-AG in comparison to existing algorithms LQ, MRS, PFQ, CQS, SRPT, and OAR. Simulations are repeated with different topologies and the presented results are average values over 10 topologies. As depicted in Figure 6, proposed

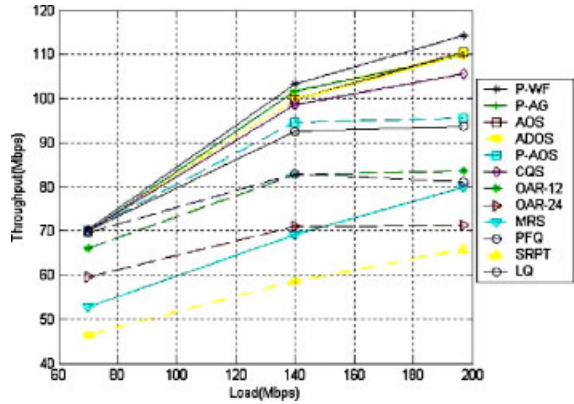


Fig. 6. Throughput performance of schedulers in 802.11n.

AOS and ADOS algorithms significantly outperform all the existing algorithms in terms of throughput, e.g., by 53% over SRPT, by 35% over MRS, PFQ, and by 21% over LQ, as they both maximize the instantaneous throughput. Our predictive block schedulers, P-AG and P-WF provide a further improvement of 4–5% over AOS/ADOS schemes, since they maximize the throughput in the long term. AOS/ADOS, P-WF, and P-AG provide the highest throughput as they possess the most explicit insight about the system behavior, considering the effects of the physical medium, MAC efficiency and queue states jointly. It is worthwhile to note that throughput performance of ADOS is close to AOS, implying that the algorithm can be applied after rate matching.

In Figure 7, the MAC efficiency, i.e., the ratio of the average observed throughput to average data rate (both averaged in time and across users) is plotted together for the maximum load level (200 Mbps) for each scheduler, when the system is in saturation. This figure illustrates that LQ and CQS algorithms operate with highest efficiencies, since the average

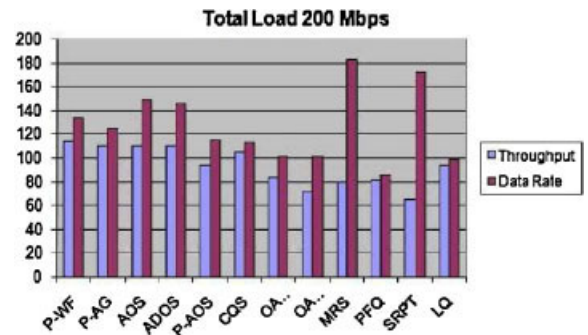


Fig. 7. Average throughput and data rate of schedulers in a saturated 802.11n network.

throughput is close to average of physical data rates, but the obtained throughput level is lower than our proposed schemes. SRPT and MRS are the most inefficient schemes, since the average throughput is less than half of the average of selected user data rates. All our proposed schemes provide the highest throughput with considerably high efficiency, implying that the system capacity is exploited while maximizing throughput.

Next, we evaluate fairness of the schedulers. For this purpose, we define an unfairness index as the ratio of the standard deviation of station throughput to the mean throughput, i.e.,  $UF = \sigma/S_{av}$ . It is obvious that the larger UF gets, the distribution of throughput among stations becomes more *unfair*. Using the definition of this unfairness index, a picture of the fairness performance of all algorithms under varying load has been obtained as depicted in Figure 8. Figure 8a shows fairness performance of existing schedulers, while Figure 8b involves unfairness index for proposed schemes, both as a function of increasing load. SRPT and MRS algorithms show the poorest performance in terms of fairness, since they aggressively favor users with high channel capacities. The LQ algorithm is the fairest scheme as it operates like the round-robin scheme providing equal access to each station. CQS algorithm follows the LQ algorithm, but with a higher unfairness index. Fairness of our proposed algorithms remains between the performance of CQS and MRS. AOS is the most unfair among proposed schemes, since instantaneous throughput is maximized in an opportunistic fashion. The ADOS algorithm offers slightly more fair distribution than AOS, due to the fact that quantized data rates results in increased emphasis on queue sizes, enhancing fairness. Our predictive block schedulers, P-WF and P-AG, improve fairness further in addition to providing the highest throughput, and especially P-AG has a lower unfairness index since it provides access guarantees to all users. Among proposed schemes P-AOS, which employs throughput opportunistic scheduling in a proportional manner, has the lowest unfairness index with a performance close to PFQ and OAR schemes. The similar level of fairness of P-AOS, PFQ, and OAR schemes is due to temporal criteria in their decision metrics. When throughput and fairness performance are considered together, our predictive block schedulers, P-WF and P-AG, stand out as the best scheduling schemes that provide the highest throughput without fairness penalty.

Finally, we evaluate the delay performance of the schedulers in Figure 9. The average delay is plotted

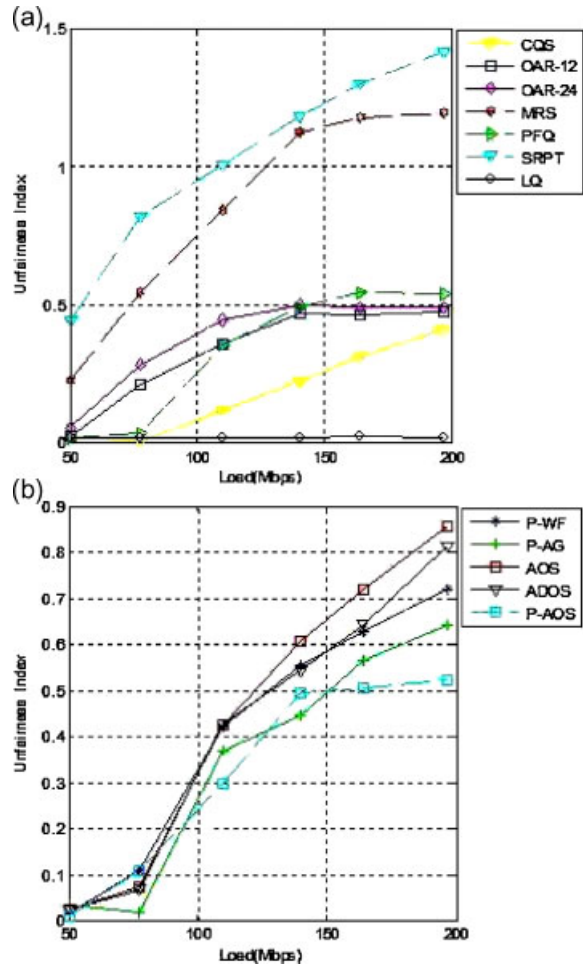


Fig. 8. Fairness performance of (a) existing, (b) proposed schedulers in 802.11n.

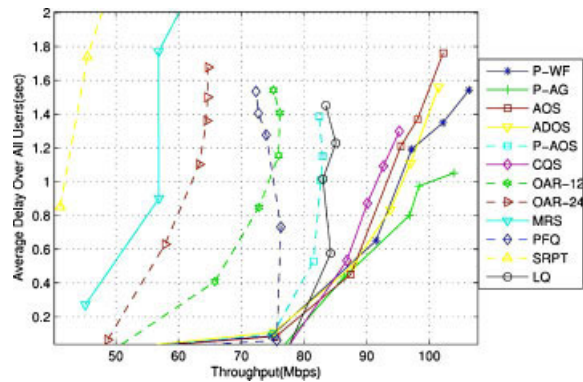


Fig. 9. Delay-throughput performance of schedulers in 802.11n.

against observed throughput for each scheduling algorithm. The simulations were carried out for a duration of 5 s. Opportunistic schedulers MRS and SRPT fail in terms of delay since they do not serve a considerably large amount of users. (While evaluating delay performance for those users, we assume that their average delays are equal to the simulation duration, 5 s.) AOS and P-WF provide lower delay but the average delay is slightly larger than fair schedulers such as CQS and LQ. In addition to providing access guarantees at high throughput values, the P-AG algorithm always provides the lowest mean user delay.

In terms of complexity, our instantaneous schedulers, AOS, ADOS, and P-AOS, are scalable with increasing number of nodes, since the computational complexity is linearly increasing with number of nodes. Considering the predictive schedulers, the complexity of P-AG is also linear. On the other hand, the P-WF algorithm involves some operations which might be difficult to scale for a very large number of nodes.

All our schedulers provide throughput closed to available data rates offered by 802.11n air interface at the user level. Our predictive algorithms, P-WF and P-AOS provide the best compromise in delay-throughput performance, at some complexity cost. P-WF maximizes throughput among all schedulers and P-AG offers very high throughput values while providing the lowest average user delay. Traditional greedy opportunistic schedulers fail considerably in the presence of actual system overhead and frame aggregation.

## 6. Conclusions

In this work, we propose a family of scheduling algorithms, namely AOS, ADOS, P-AOS, P-WF, and P-AG schemes for next generation WLANs. Our algorithms perform scheduling decisions based on throughput, calculated instantaneously or considering the long-term evolution of user queues. We provide a performance comparison of our schemes with the outstanding algorithms from the literature considering all in the same air interface for the first time. We show that with frame aggregation, which is an important feature of 802.11n, spatially greedy scheduling algorithms are no longer optimal for maximizing throughput performance. Even though these algorithms yield the maximum physical data rates and they would have provided the highest throughput values in an infinitely backlogged setting if there were no overhead, they all fail considerably under the 802.11n model. Our

AOS and ADOS algorithms improve this picture by bringing the observed throughput close to available rates. Proportional AOS (P-AOS) provides better fairness at the expense of lower throughput. Our block scheduling algorithms, P-WF and P-AG, improve the throughput further due to the main objective of long-term throughput maximization and they also provide fairness and lower delay due to multi-user scheduling. In particular, P-WF offers the highest throughput, and P-AG provides the lowest average user delay among all schedulers.

Our algorithms facilitate the application of 802.11n technology in next generation WLANs and WMNs due to throughput maximization with bounded delay and fairness and low complexity. The practical implementation requires monitoring of load, queue, and channel states at each user, all of which can be easily handled in current chips and drivers. Extensions for QoS support is left as future work, where approaches such as Reference [11] can be applied to impose specific QoS requirements.

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