Cross-layer Design of MIMO-enabled WLANs with Network Utility Maximization

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Abstract—Wireless local area networks (WLANs) have become a ubiquitous high-speed data access technology. The recent IEEE 802.11e standard provides quality of service (QoS) support, and the pending 802.11n standard further increases the transmission rate by using the multiple-input-multiple-output (MIMO) technique. Multiple antennas can be used to improve the performance gain by either increasing the transmission reliability through spatial diversity or increasing the transmission rate through spatial multiplexing. This new characteristic at the wireless physical layer requires the corresponding adaptation at the medium access control (MAC) layer to reach the best performance gain. In this paper, we propose cross-layer design schemes for WLANs under two different MAC protocols: the carrier sense multiple access with collision avoidance (CSMA/CA)-based 802.11e MAC, and the slotted Aloha MAC. For the 802.11e MAC, two different contention window size adaptation schemes, namely *U-MAC* and *D-MAC*, are proposed, which facilitate the MAC protocol to adapt its contention window size jointly with the physical layer's MIMO operating parameters. For the slotted Aloha MAC, a cross-layer optimization framework *NUM-O* is proposed for jointly optimizing the MIMO configuration at the physical layer and the persistent probabilities for different classes of multimedia traffic at the MAC layer. A distributed algorithm *NUM-D* based on dual decomposition and a simplified version *NUM-S* are also proposed. Simulation results are presented to show the effectiveness of the proposed methods.

Index Terms—WLANs, 802.11e, MIMO, slotted Aloha, network utility maximization, optimization.

I. INTRODUCTION

In recent years, there has been a tremendous growth in adopting the IEEE 802.11 standards for high-speed wireless local area networks (WLANs). The recent 802.11e medium access control (MAC) protocol [1] can provide differentiated quality-of-service (QoS) support via the Enhanced Distributed Channel Access (EDCA) function. In EDCA, the traffic is classified into four access categories (ACs), where each AC has different priority for channel access based on its own Arbitration Inter-Frame Space (AIFS), transmission opportunity values, and minimum and maximum contention window (CW) sizes. Among these parameters, the minimum contention window size has been shown to have a major impact on the network performance [2]. Various schemes have been proposed to tune the contention window size in order to improve the

MAC efficiency [3]. The recent 802.11n proposal [4] aims to increase the physical link data rate up to 600 Mbps, by using the multiple-input-multiple-output (MIMO) technology at the physical layer [5]. In a wireless fading channel, two major performance gains can be realized with a wireless MIMO system: the *diversity gain* and *spatial multiplexing gain* [6].

Some recent work has studied the multiplexing and diversity gains of wireless MIMO systems under different cross-layer frameworks. A MIMO-enabled MAC protocol was proposed in [7], where the protocol mitigates interferences by utilizing the multiplexing capability of the MIMO system. Another MIMO-enabled MAC protocol based on CSMA/CA in an ad-hoc network was proposed in [8], where the MAC layer schedules the transmission of different spatial streams by utilizing the spatial multiplexing capability of the MIMO system. The MIMO antenna's spatial beamforming capability is utilized in [9] by the proposed SPACE-MAC protocol.

Some other schemes allow the system to adaptively switch between the two MIMO working modes. The adaptive routing protocol in [10] directs a link to operate under full spatial diversity gain when the distance is long and the signal is weak. It operates under maximal spatial multiplexing gain when the distance is short and the signal is strong so as to increase the throughput. The transmission control protocol (TCP) over wireless MIMO channel is shown to perform better with a more reliable link provided by the diversity gain of a space-time block coding system at low SNR regions, while a spatial multiplexing scheme outperforms in the high SNR regions [11]. All the cross-layer designs summarized above only focus on utilizing one of the two MIMO resources at a time: either full diversity or full spatial multiplexing. But it is not possible to realize both maximal diversity gain and maximal spatial multiplexing gain simultaneously. Apart from the two working modes where we can obtain a maximal multiplexing gain r while the diversity gain d is zero (or vice versa), there are intermediate working modes where we can achieve part of the diversity gain and multiplexing gain simultaneously. This is called the diversity-multiplexing tradeoff. It is intuitive to consider whether adaptively tuning the MIMO system is more beneficial than only choosing either the maximal multiplexing or the maximal diversity gain.

Some recent schemes investigated the possibility of achieving the diversity-multiplexing tradeoff. Lu and Kumar constructed a space-time block code to achieve any integer point on the multiplexing-diversity tradeoff curve [12]. In [13], Lee *et al.* studied the optimal tradeoff in a MIMO ad-hoc network by formulating the rate-reliability tradeoff problem as a network utility maximization problem. However, only one

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class of traffic is considered, and the MAC uses a reservation-based scheduling scheme, where the transmission time by each node has to be allocated in advance.

Network utility maximization (NUM) has been shown to be an effective method to tackle cross-layer optimization problems in wireless networks [14]. The utility function for each source node is usually chosen such that it reflects the satisfaction attained by the user for the services that it receives. When the NUM formulation satisfies certain conditions, such as being a separable convex optimization problem, fully distributed algorithms can be obtained, which are highly desirable in today's distributed networking environment.

In this work, we consider how to best utilize this multiplexing-diversity tradeoff in WLANs with MIMO channels. We formulate the cross-layer design as NUM problems, where the MAC layer parameters and the multiplexing-diversity tradeoff at the physical layer are jointly optimized. Two types of MAC protocols are studied in this paper, the carrier sense multiple access with collision avoidance (CSMA/CA) MAC, which is used by the 802.11e EDCA, and the slotted Aloha MAC. These are two of the most widely used random access protocols. For 802.11's CSMA/CA MAC, a centralized scheme is proposed with the access point being the centralized controller. For the slotted Aloha MAC, we construct a similar model based on the EDCA MAC model. The Aloha MAC provides us with a more accurate throughput model, which enables us to include hard QoS constraints into the NUM formulation. We further convert the Aloha MAC problem into a separable dual problem and propose a distributed algorithm to solve it.

To formulate the 802.11e-based WLAN with MIMO channels as a NUM problem, we first need to find an appropriate system model. Most of the research work in this area has focused on the saturation throughput analysis of the 802.11 WLAN, which is the maximum load that the system can carry in the saturated condition (i.e., the transmission queue of every station is assumed to be always nonempty). This is a fundamental performance figure which indicates the stable limit of the network throughput when the offered traffic load increases. Simulation studies [15] and experimental testbeds [16] have been constructed to analyze the throughput performance of EDCA. Analytical models are also proposed (e.g., [17]–[19]).

One major obstacle to utilize the above models for NUM formulation is their computational complexity, which usually involves solving a set of non-linear equations. To facilitate practical implementation, it is preferable to use a closed-form expression for the throughput in the utility optimization problem. As a result, in this paper, we propose two 802.11e EDCA throughput models based on several simplifying assumptions. These assumptions provide us an EDCA model where the saturation throughput can be derived with a closed-form solution. This greatly facilitates the NUM formulation, and improves the convergence speed of the optimization problem. Although the simplifying assumptions may reduce the accuracy of the model, simulation results show the effectiveness of the proposed schemes, and verify that the simplifying assumptions provide a good trade-off to obtain the solutions.

The contributions of our work are as follows:

- 1) For 802.11e WLANs with MIMO channels, we propose two cross-layer schemes, namely *U-MAC* and *D-MAC*, which jointly select the MIMO coding scheme at the physical layer and the minimum contention window size at the MAC layer to achieve the maximal network utility.
- 2) For the slotted Aloha based WLAN, we propose a cross-layer design framework *NUM-O* which jointly selects the MIMO coding scheme at the physical layer and the transmission persistent probability at the MAC layer to achieve the maximal network utility. By using the dual decomposition method, we then propose a distributed algorithm *NUM-D*. We further propose another algorithm called *NUM-S*, which is also practical for implementation.
- 3) Simulation results are presented to study the effectiveness of the proposed schemes. The *U-MAC* and *D-MAC* schemes are compared with the original 802.11e EDCA protocol under MIMO channels. Both system throughput and delay performance are shown to improve significantly. For the slotted-Aloha MAC, network throughput and reliability performance of the distributed *NUM-D* scheme is compared to the *NUM-S* scheme.

The comparison between our proposed algorithms is shown in Table I. The rest of the paper is organized as follows. System models and the cross-layer optimization schemes *U-MAC* and *D-MAC* for the 802.11e WLAN are presented in Section II. Section III proposes the system model *NUM-O* for the slotted Aloha based WLAN, and its distributed solution *NUM-D*. Simulation results are presented in Section IV. Conclusions and future work are given in Section V.

II. SYSTEM MODEL FOR 802.11e EDCA MAC

Consider a WLAN with an access point (AP). Let $\mathcal{N}$ denote the set of wireless stations. According to the EDCA specifications in the 802.11e standard, there can be up to four different classes of traffic with different QoS requirements. For simplicity, we study the case of two access categories (AC_1 and AC_2) with AC_2 being the higher priority traffic in the network. We use $\mathcal{N}_1$ and $\mathcal{N}_2$ to denote the set of wireless stations in AC_1 and AC_2 , respectively. Each wireless station transmits one class of traffic, so the set of all stations $\mathcal{N}$ is $\mathcal{N}_1 \cup \mathcal{N}_2$. We use N_1 , N_2 , and N to denote the number of stations in the set. Thus, $N_1 = |\mathcal{N}_1|$, $N_2 = |\mathcal{N}_2|$, and $N = |\mathcal{N}|$. N_1 , N_2 and N are assumed to be known constants in the system model. Estimation of the number of competing nodes in the network has been studied in [20], [21], and is beyond the scope of this paper. Extension to four access categories is fairly straightforward based on the optimization framework proposed below.

We study the performance of wireless stations competing for channel access and sending data to the AP. Each wireless station has M_T transmit antennas, and the AP has M_R receive antennas. There is a fundamental tradeoff between a MIMO system's multiplexing and diversity gains. For each spatial multiplexing gain r , the best diversity gain $d^*(r)$ is the supremum of the diversity gain achieved over all schemes. In a Rayleigh-fading channel with long enough block lengths,

TABLE I
COMPARISON BETWEEN PROPOSED SCHEMES

Scheme	Operation	MAC	Input Parameters	Variables	Output Solutions	Comments
<i>U-MAC</i>	Centralized	CSMA/CA	$M_T, M_R, \alpha, \beta, \mathcal{N}, L$ $k_c, k_p, \gamma, T_{hdr}, T_{ACK}$ $T_{slot}, T_{SIFS}, T_{AIFS}$	$\mathbf{x}, \mathbf{y}, \mathbf{r}, \bar{W}_a$	PHY: $\mathbf{r}$ MAC: $\bar{W}_a$	Uniform CW for each AC.
<i>D-MAC</i>	Centralized	CSMA/CA	$M_T, M_R, \alpha, \beta, \mathcal{N}, L$ $k_c, k_p, \gamma, T_{hdr}, T_{ACK}$ $T_{slot}, T_{SIFS}, T_{AIFS}$	$\mathbf{x}, \mathbf{y}, \mathbf{r}, W_s$	PHY: $\mathbf{r}$ MAC: W_s	Differentiated CW for each station.
<i>NUM-O</i>	Centralized	Slotted Aloha	$M_T, M_R, \alpha, \beta, \mathcal{N}$ k_c, k_p, γ, R	$\mathbf{x}, \mathbf{y}, \mathbf{r}, \mathbf{p}$	PHY: $\mathbf{r}$ MAC: $\mathbf{p}$	Centralized NUM formulation.
<i>NUM-D</i>	Distributed	Slotted Aloha	$M_T, M_R, \alpha, \beta, \mathcal{N}$ k_c, k_p, γ, R	$\mathbf{x}', \mathbf{y}, \mathbf{r}$ $\mathbf{p}', \mathbf{p}'', \boldsymbol{\lambda}, \boldsymbol{\mu}$	PHY: $\mathbf{r}$ MAC: $\mathbf{p}$	Distributed solution for <i>NUM-O</i> .
<i>NUM-S</i>	Distributed	Slotted Aloha	$M_T, M_R, \alpha, \beta, \mathcal{N}$ k_c, k_p, γ, R	$\mathbf{x}, \mathbf{y}, \mathbf{r}, \mathbf{p}$	PHY: $\mathbf{r}$ MAC: $\mathbf{p}$	Simplified scheme as performance baseline.

the optimal multiplexing-diversity tradeoff $d^*(r)$ is given by the piecewise-linear function connecting the points $(r, d^*(r))$, for $r = 0, 1, \dots, \min(M_T, M_R)$ [22]:

$$d^*(r) = (M_T - r)(M_R - r), \quad (1)$$

where M_T and M_R are the number of transmit and receive antennas, respectively. In this paper, we assume that a family of carefully designed codes can achieve the above optimal tradeoff performance. However, this curve is non-differentiable, which may cause difficulties to solve the NUM problem. We use the differentiable approximation as in [13]:

$$d(r) = (M_T - r)(M_R - r), \quad 0 \leq r \leq \min(M_T, M_R). \quad (2)$$

This differentiable approximation is a lower bound of (1), which gives a subset of the feasible diversity-multiplexing tradeoff region. Although this can potentially lead to a sub-optimal solution of the problem due to the reduced tradeoff region, as analyzed in [13], this approximation is close to the exact tradeoff relationship and the reduction of the feasible tradeoff region is small. Thus, the impact on the results should not be significant.

If a wireless link from the wireless station $s \in \mathcal{N}$ to the AP has the average signal-to-noise ratio γ_s , multiplexing gain r_s and diversity gain d_s , then the link data rate $c_s(\gamma_s)$ (bps) and error probability $p_s^{err}(\gamma_s)$ can be approximated as [23]:

$$c_s(\gamma_s) = k_c r_s \log \gamma_s, \quad (3)$$

and

$$p_s^{err}(\gamma_s) = k_p \gamma_s^{-d(r_s)}, \quad (4)$$

where k_c and k_p are positive constants for different coding schemes. The log function uses base 2 throughout this paper. The multiplexing gain r_s and diversity gain d_s conform to the optimal tradeoff in (2). Then, the link transmission reliability y_s is:

$$y_s = 1 - k_p \gamma_s^{-d(r_s)}, \quad s \in \mathcal{N}. \quad (5)$$

With c_s being the data rate of wireless station s , the achievable throughput of each station is usually significantly lower than c_s due to the random access and the protocol overhead [2]. To formulate the NUM problem, we need an analytical model for the throughput of each station with respect to c_s and other network parameters, which is a difficult task due to

the CSMA/CA based access scheme. However, the saturation throughput is more tractable and has been successfully derived from various mathematical models.

For a single cell 802.11 WLAN, its saturation throughput is a good indicator of network performance because it is the sustainable throughput under heavy traffic load, and is also close to the maximum network capacity. In this work, we base our analysis on the saturation network performance. There are two causes of packet loss in an 802.11 WLAN. One is the packet collision where two nodes transmit simultaneously. The other one is channel error, where a packet is received without packet collisions, but is corrupted due to low SNR.

In this paper, we denote the saturation throughput under an ideal channel (i.e., no channel errors) as x_s . Then, $x_s y_s$ can approximately represent the effective throughput after further discarding the corrupted packets due to channel errors. This approximation separates the effects of packet collision and channel error on the throughput calculation, and greatly facilitates the problem formulation.

The throughput x_s is primarily a function of the physical layer parameters, such as the network basic and data rates, and the MAC layer parameters such as contention window sizes, the DIFS/SIFS/AIFS values, and the frame header overhead. Of all the elements listed above, we focus on studying the effects of the data rate c_s and the minimum contention window size W_s for station s in this paper. The data rate with a MIMO channel is given by (3), and it is a function of the SNR γ_s and the MIMO operation mode r_s .

We consider two cases of the assignment of W_s . In the first case, there is a uniform CW value for each AC, where all wireless stations belonging to the same AC use the same minimum contention window value. This is the normal behavior in 802.11e. We call this MAC as the Uniform-CW MAC or *U-MAC*. In the second case, we allow each wireless station to freely choose its own minimum contention window size without conforming to the same CW in its AC. We call this MAC as the Differentiated-CW MAC or *D-MAC*.

Time is partitioned into virtual time slots where each slot can be either a backoff time slot, a collision-free transmission slot, or a collided transmission slot. The probability for station s to transmit in a virtual time slot can be approximated as

follows [24]:

$$\tau_s = \frac{2}{W_s + 1}, \quad s \in \mathcal{N}, \quad (6)$$

where W_s is the minimum contention window size for station s . The probability that one transmitted packet by station s will collide is the probability that any of the other stations also transmit:

$$q_s = 1 - \prod_{k \in \mathcal{N}, k \neq s} (1 - \tau_k), \quad s \in \mathcal{N}. \quad (7)$$

In the following subsections, we describe how to determine the throughput x_s for the two MAC schemes separately below.

A. Saturation Throughput Analysis of the U-MAC Scheme

For the *U-MAC*, τ_s and q_s in (6) and (7) are reduced to the same values for each AC, as we require that each AC has a uniform minimum contention window size, which is $W_s = \bar{W}_a$, for wireless station s transmitting AC_a traffic. Thus from (6), we can use τ_a to represent any τ_s , $s \in \mathcal{N}_a$, for $a = 1, 2$. To calculate x_s , we extend the mean value based saturation throughput analysis in [25]. The main difference here is that the wireless stations may use different data rates other than the uniform data rate assumed in [25]. The average length of one virtual time slot T_a for AC_a (where $a = 1, 2$) can be approximated as follows:

$$T_a = \sum_{s \in \mathcal{N}_a} \frac{\tau_s}{\sum_{k \in \mathcal{N}_a} \tau_k c_s} \frac{L}{c_s} + T_{hdr} + T_{SIFS} + T_{ACK} + T_{AIFS} + \frac{\bar{W}_a}{N_a + 1} T_{slot}, \quad a = 1, 2, \quad (8)$$

where T_{hdr} , T_{ACK} , T_{slot} , T_{SIFS} and T_{AIFS} denote the length of the frame header, the ACK frame, the backoff time slot length, the SIFS and AIFS length, respectively. $\bar{W}_a$ (for $a = 1, 2$) represents the minimum contention window size of AC_a . This paper focuses on studying the effects of contention window size adaptation, and thus the same AIFS is used for each AC. An identical payload length L is assumed for the network. L/c_s is the time to transmit the frame payload of station s . The average payload transmission time is the weighted sum of all AC_a stations, using each station's transmission probability as the weight.

From [25], we can calculate the rate of success for AC_a , which is the average number of collision-free transmissions by AC_a per second, as follows:

$$v_a = \frac{N_a \tau_a (1 - q_a)}{(1 - q_1/2) N_1 \tau_1 T_1 + (1 - q_2/2) N_2 \tau_2 T_2}, \quad a = 1, 2. \quad (9)$$

The aggregated saturation throughput of all stations belonging to AC_a is equal to $v_a L$. The saturation throughput for station s in each AC can be calculated as follows:

$$\hat{x}_s = v_a L \frac{c_s(\gamma_s)}{\sum_{i \in \mathcal{N}_a} c_i(\gamma_i)}, \quad \forall s \in \mathcal{N}_a, \quad a = 1, 2. \quad (10)$$

The above equation shows that the individual saturation throughput of each station s in AC_a is the weighted portion of $v_a L$ in proportion to its data rate c_s .

B. Saturation Throughput Analysis of the D-MAC Scheme

For the *D-MAC*, we allow each station s to choose its own W_s value individually based on its link state and class of traffic. In this case, we have an 802.11e WLAN with multiple data rates, and multiple CW values. To model this system accurately is a challenging task. Even for the basic 802.11e MAC with a single data rate, complicated multi-dimensional Markov chain and queueing models have to be used, which result in complex systems of non-linear equations to solve for the throughput x_s [18]. Although these models give accurate results, they usually require some stringent assumptions, and none can handle a versatile system where each wireless station has a distinct data rate and a distinct CW.

However, we may not need a highly accurate throughput model for the NUM framework to work properly. Other factors, such as the convergence speed of the optimization problem and the computation efficiency, are important for a NUM problem. It is preferable to obtain a closed form expression of x_s instead of a system of nonlinear equations on x_s . With this goal, we propose that the throughput of station s be modeled as:

$$\hat{x}_s = \Gamma \tau_s (1 - q_s) \frac{L}{T_a}, \quad s \in \mathcal{N}_a, \quad a = 1, 2, \quad (11)$$

where Γ is a positive scaling factor. Here, we assume that the two ACs have the same scaling factor. In Section II-D, we can see that the exact value of Γ need not be known for solving our NUM problem. By extending the model from [25] with approximating the uniform contention window size with $\sum_{s \in \mathcal{N}_a} W_s / N_a$, the average virtual slot length T_a (for $a = 1, 2$) is defined as follows:

$$T_a = \sum_{s \in \mathcal{N}_a} \frac{\tau_s}{\sum_{k \in \mathcal{N}_a} \tau_k c_s} \frac{L}{c_s} + T_{hdr} + T_{SIFS} + T_{ACK} + T_{AIFS} + \frac{\sum_{s \in \mathcal{N}_a} W_s}{N_a(N_a + 1)} T_{slot}, \quad a = 1, 2, \quad (12)$$

where we use the average contention window size $\sum_{s \in \mathcal{N}_a} W_s / N_a$ as an approximation of the identical contention window size modeled in [25].

Equation (11) states that the throughput of wireless station s is in proportion to its transmission probability τ_s , collision-free probability $(1 - q_s)$, and the average transmission rate of one payload by each AC_a (L/T_a). This is a reasonable throughput approximation as the transmission and collision probabilities of a station are the major factors influencing its throughput. The linear proportional relationship is a bold assumption. From our later simulation results, we can verify that our NUM formulation based on this simple assumption can efficiently achieve the desired traffic differentiation and utility optimization effects.

C. Network Utility Formulation

We use the following α -fair utility function [26]:

$$U(x) = \begin{cases} (1 - \alpha)^{-1} x^{(1 - \alpha)}, & \text{if } \alpha \in (0, 1) \cup (1, \infty), \\ \log x, & \text{if } \alpha = 1, \end{cases} \quad (13)$$

where α is the *fairness* parameter. If x is the throughput of the source node, then $\alpha \rightarrow 0$ leads to throughput maximization. Proportional and harmonic mean fairness are achieved when $\alpha = 1$ and $\alpha = 2$, respectively. When $\alpha \rightarrow \infty$, max-min fairness can be achieved. In our NUM framework, we choose the utility function for each wireless station s with $\alpha > 1$:

$$U_a(x_s, y_s) = (1 - \alpha)^{-1} (x_s y_s)^{1-\alpha}, \quad \alpha > 1, \quad a = 1, 2 \quad (14)$$

where $x_s y_s$ is the effective throughput of station s after accounting for both packet collisions and channel errors. U_a represents the utility function of AC_a for $a = 1$ and 2 .

The network utility function is defined as:

$$U(\mathbf{x}, \mathbf{y}) = \sum_{i \in \mathcal{N}_1} \beta U_1(x_i, y_i) + \sum_{j \in \mathcal{N}_2} (1 - \beta) U_2(x_j, y_j), \quad \alpha > 1, \quad (15)$$

where β is an adjustable parameter between 0 and 0.5 to tune the weight of AC_1 and AC_2 on the network utility. It can be proven that $U(\mathbf{x}, \mathbf{y})$ is a concave function of $\mathbf{x}, \mathbf{y}$.

D. NUM Framework for Cross-layer Design

With the above system model and definition of the network utility, we propose our NUM formulation for cross-layer design of a MIMO-enabled 802.11e WLAN, where each station's MIMO multiplexing gain at the physical layer and the contention window sizes at the MAC layer are jointly optimized.

1) *U-MAC*: Wireless stations use the minimum contention window size of W_a in AC_a . The NUM problem can be formulated as follows:

$$\begin{aligned} \max_{\mathbf{x}, \mathbf{y}} \quad & \sum_{i \in \mathcal{N}_1} \beta U_1(x_i, y_i) + \sum_{j \in \mathcal{N}_2} (1 - \beta) U_2(x_j, y_j) \\ \text{st} \quad & 0 \leq x_s \leq v_a L \frac{c_s(\gamma_s)}{\sum_{n \in \mathcal{N}_a} c_n(\gamma_n)}, \quad \forall s \in \mathcal{N}_a, \quad a = 1, 2 \\ & \tilde{y}_a \leq y_s \leq 1 - k_p \gamma_s^{-(M_T - r_s)(M_R - r_s)}, \\ & \quad \forall s \in \mathcal{N}_a, \quad a = 1, 2 \\ & 0 \leq r_s \leq \min(M_T, M_R), \quad \forall s \in \mathcal{N} \\ & \tilde{W}_a \leq W_s \leq \hat{W}_a, \quad a = 1, 2, \end{aligned} \quad (16)$$

where v_a is given by (9), and is a function of $\bar{W}_a$, r_s and other system parameters. The parameters $\tilde{y}_a$, $\tilde{W}_a$ and $\hat{W}_a$ are constant bounds on the variables, and should be selected within reasonable ranges. The above problem is a NUM problem with variables $\mathbf{x}, \mathbf{y}, \mathbf{r}$ and $\bar{W}_a$. The saturation throughput from (10) is used as the upperbound for x_s .

Although the objective function in (16) is concave, the constraint sets make this problem non-convex and challenging to solve. However, our tests with Matlab's nonlinear optimization toolbox, using the sequential quadratic programming (SQP) method [27], show that this problem formulation, under reasonable ranges of network parameters and initial variable values, has no difficulty in converging to a unique solution. Results from Section IV show that the number of iterations needed is in the range of 20 to 200. Note that due to non-convexity of the problem, the solution can be sub-optimal in

the sense that a local instead of the global optimal solution is determined. When the link SNR values drop below certain levels, the problem may no longer have a feasible solution. Analytically deriving the feasible region of the NUM problem is difficult. However, from an engineering point of view, whenever a feasible solution is unavailable, it means that one or more of the stations with the lowest SNRs will not satisfy the minimum QoS requirements. There are two possible actions to take: reducing the QoS demand or disassociating those stations from the network. To study these scenarios in detail is beyond the scope of the current paper and will be subject of our future study.

2) *D-MAC*: With each station s choosing its minimum contention window size W_s individually, the NUM problem can be formulated as follows:

$$\begin{aligned} \max_{\mathbf{x}, \mathbf{y}} \quad & \sum_{i \in \mathcal{N}_1} \beta U_1(x_i, y_i) + \sum_{j \in \mathcal{N}_2} (1 - \beta) U_2(x_j, y_j) \\ \text{st} \quad & 0 \leq x_s \leq \Gamma \tau_s (1 - q_s) \frac{L}{T_a}, \quad \forall s \in \mathcal{N}_a, \quad a = 1, 2 \\ & \tilde{y}_a \leq y_s \leq 1 - k_p \gamma_s^{-(M_T - r_s)(M_R - r_s)}, \\ & \quad \forall s \in \mathcal{N}_a, \quad a = 1, 2 \\ & 0 \leq r_s \leq \min(M_T, M_R), \quad \forall s \in \mathcal{N} \\ & \tilde{W}_s \leq W_s \leq \hat{W}_s, \quad \forall s \in \mathcal{N}, \end{aligned} \quad (17)$$

where $\hat{W}_s$ and $\tilde{W}_s$ are the lower and upper bounds of the contention window for station s , respectively. The variables τ_s , q_s , and T_a are given in (6), (7) and (12). Note that for the constant parameter Γ , it ends up being a scaling factor $\Gamma^{1-\alpha}$ in the objective function as defined by (15), and has no effect on the optimal solutions, which are the system's minimum contention window size W_s and the MIMO multiplexing gain r_s . The above problem is a NUM problem with variables $\mathbf{x}, \mathbf{y}, \mathbf{r}$, and W_s . It can also be solved using standard algorithms for constrained nonlinear optimization problems as discussed in Section II-D.1.

With the above formulation, the AP in an 802.11e WLAN can collect each station's link SNR, select a β with appropriate network revenue models, and solve either (16) or (17) to obtain the MIMO multiplexing gain r_s and minimum contention window size W_s for each station. The resulting r_s and W_s values can be sent out in the EDCA parameter set elements of the 802.11e beacon frame for each station to adjust its physical and MAC layer operation parameters.

III. SYSTEM MODEL FOR SLOTTED ALOHA MAC

In this section, we consider the slotted Aloha MAC. The NUM formulation can be transformed to a separable convex optimization problem, and a distributed algorithm can be derived accordingly. For the slotted Aloha, we can obtain the throughput formulation without assuming the saturated conditions. When source node s transmits with persistent probability p_s in slotted Aloha, its throughput is:

$$x_s = c_s(\gamma_s) p_s \prod_{k \in \mathcal{N}, k \neq s} (1 - p_k), \quad s \in \mathcal{N}. \quad (18)$$

The transmission reliability y_s is the same as in (5). Instead of only differentiating the priority of AC_1 and AC_2 traffic, we

further assume that the higher priority traffic (AC_2) is real-time traffic with constant-bit-rate (CBR) flows, which has a hard throughput requirement R and reliability demand Q :

$$\begin{aligned} R &\leq x_j \leq \hat{x} = k_c \hat{r} \log \hat{\gamma}, & j &\in \mathcal{N}_2, \\ Q &\leq y_j \leq 1, & j &\in \mathcal{N}_2, \end{aligned} \quad (19)$$

where $\hat{x}$ is the constant upper bound on throughput, with $\hat{r}$ and $\hat{\gamma}$ being the network's maximum multiplexing gain and maximum SNR value, respectively. The maximum SNR value can either be deduced from the network channel condition under study or be assigned a high enough value to put a reasonable upper bound in the problem formulation.

The AC_1 traffic is best-effort traffic, and also has the bounding constraints:

$$\begin{aligned} \tilde{x}_1 &\leq x_i \leq \hat{x}, & i &\in \mathcal{N}_1, \\ \tilde{y}_1 &\leq y_i \leq 1, & i &\in \mathcal{N}_1, \end{aligned} \quad (20)$$

where $\tilde{x}_1$ and $\tilde{y}_1$ are the constant lower bound on throughput and reliability for best-effort traffic, respectively.

A. Network Utility Formulation

To differentiate the different QoS requirement of AC_1 and AC_2 , we use the utility function of (13) with $\alpha > 1$, and extend it to include a normalizing denominator. Thus, the utility function for the wireless stations with AC_1 traffic is as follows:

$$U_1(x_i, y_i) = \frac{(x_i y_i)^{1-\alpha} - (\tilde{x}_1 \tilde{y}_1)^{1-\alpha}}{(\hat{x})^{1-\alpha} - (\tilde{x}_1 \tilde{y}_1)^{1-\alpha}}, \quad \alpha > 1 \quad (21)$$

where the product $x_i y_i$ can be interpreted as the effective throughput for the best-effort station $i \in \mathcal{N}_1$.

For the CBR traffic in AC_2 , the utility function is chosen to be a function of the reliability only, because we expect that the throughput x will satisfy the CBR traffic's throughput demand R as in (19); however, further increasing a CBR traffic's throughput provisioning usually does not provide additional performance gains:

$$U_2(y_i) = \frac{y_i^{1-\alpha} - Q^{1-\alpha}}{1 - Q^{1-\alpha}}, \quad \alpha > 1. \quad (22)$$

The utility functions in (21) and (22) are normalized such that $U_1(\tilde{x}_1, \tilde{y}_1) = U_2(Q) = 0$ and $U_1(\hat{x}, 1) = U_2(1) = 1$. This avoids the apparent problem of combining two utility functions, which would otherwise have a few magnitude of difference in value. The network utility is the sum of the utilities of all the source nodes:

$$\begin{aligned} U(\mathbf{x}, \mathbf{y}) &= \sum_{i \in \mathcal{N}_1} \beta U_1(x_i, y_i) \\ &+ \sum_{j \in \mathcal{N}_2} (1 - \beta) U_2(y_j), \quad \alpha > 1 \end{aligned} \quad (23)$$

where $\mathbf{x}, \mathbf{y}$ are vectors for each source's throughput and reliability, β is an adjustable parameter between 0 and 1 to tune the weight of AC_1 and AC_2 's utility values. It can be shown that $U(\mathbf{x}, \mathbf{y})$ is a concave function.

B. Utility-Optimal PHY/MAC Cross-layer Design

1) *Centralized Scheme: NUM-O*: We now present the centralized NUM formulation for the slotted Aloha MAC, which is called *NUM-O*. Assuming that each station s can adaptively adjust its persistent probability p_s at the MAC layer with cross-layer information from the MIMO-enabled physical layer, we propose the following utility maximization formulation:

$$\begin{aligned} \max_{\mathbf{x}, \mathbf{y}} \quad & \sum_{i \in \mathcal{N}_1} \beta U_1(x_i, y_i) + \sum_{j \in \mathcal{N}_2} (1 - \beta) U_2(y_j) \\ \text{st} \quad & x_s \leq k_c r_s \log(\gamma_s) p_s \prod_{k \in \mathcal{N} \setminus \{s\}} (1 - p_k), \quad \forall s \in \mathcal{N} \\ & y_s \leq 1 - k_p \gamma_s^{-(M_T - r_s)(M_R - r_s)}, \quad \forall s \in \mathcal{N} \\ & \tilde{x}_1 \leq x_i \leq \hat{x}, \quad \forall i \in \mathcal{N}_1 \\ & R \leq x_j \leq \hat{x}, \quad \forall j \in \mathcal{N}_2 \\ & \tilde{y}_1 \leq y_i \leq 1, \quad \forall i \in \mathcal{N}_1 \\ & Q \leq y_j \leq 1, \quad \forall j \in \mathcal{N}_2 \\ & 0 \leq r_s \leq \min(M_T, M_R), \quad \forall s \in \mathcal{N} \\ & 0 \leq p_s \leq 1, \quad \forall s \in \mathcal{N}. \end{aligned} \quad (24)$$

Problem (24) is a non-linear optimization problem with respect to the variables $\{\mathbf{x}, \mathbf{y}, \mathbf{r}, \mathbf{p}\}$. We can use a change of variables to make the problem separable into sub-problems, and prove that the resulting problem is convex. We perform a log transformation of variables: $x'_s = \log x_s$, $p'_s = \log p_s$ and $p''_s = \log(1 - p_s)$ for $s \in \mathcal{N}$ by taking log on both sides of the first constraint. The NUM problem becomes:

$$\begin{aligned} \max_{\mathbf{x}', \mathbf{y}} \quad & \sum_{i \in \mathcal{N}_1} \beta U'_1(x'_i, y_i) + \sum_{j \in \mathcal{N}_2} (1 - \beta) U_2(y_j) \\ \text{st} \quad & x'_s - \log k_c - \log r_s - \log(\log \gamma_s) \\ & - p'_s - \sum_{k \in \mathcal{N} \setminus \{s\}} p''_k \leq 0, \quad \forall s \in \mathcal{N} \\ & y_s - 1 + k_p \gamma_s^{-(M_T - r_s)(M_R - r_s)} \leq 0, \quad \forall s \in \mathcal{N} \\ & e^{p'_s} + e^{p''_s} \leq 1, \quad \forall s \in \mathcal{N} \\ & \log \tilde{x}_1 \leq x'_i \leq \log \hat{x}, \quad \forall i \in \mathcal{N}_1 \\ & \log R \leq x'_j \leq \log \hat{x}, \quad \forall j \in \mathcal{N}_2 \\ & \tilde{y}_1 \leq y_i \leq 1, \quad \forall i \in \mathcal{N}_1 \\ & Q \leq y_j \leq 1, \quad \forall j \in \mathcal{N}_2 \\ & 0 \leq r_s \leq \Delta_s, \quad p'_s, p''_s \leq 0, \quad \forall s \in \mathcal{N} \end{aligned} \quad (25)$$

where

$$\Delta_s = \min \left\{ \min\{M_T, M_R\}, \frac{M_T + M_R}{2} - \frac{1}{2} \sqrt{\frac{2}{\ln \gamma_s}} \right\}, \quad (26)$$

and

$$U'_1(x', y) = \frac{(e^{x'} y)^{1-\alpha} - (\tilde{x}_1 \tilde{y}_1)^{1-\alpha}}{(\hat{x})^{1-\alpha} - (\tilde{x}_1 \tilde{y}_1)^{1-\alpha}}, \quad (27)$$

The above problem is a convex optimization problem. The detailed proof of convexity is included in the Appendix. Appendices A and B show the proofs for the convexity of the objective function and the constraints, respectively. In order to obtain a convex problem, we introduced an extra constraint on r_s as shown in (26). This constraint can reduce

r_s 's range of values in low SNR conditions. However, this reduction in the range of r_s is not significant. For example, when $M_T = 2$, $M_R = 3$, and $\gamma_s = 7$ dB, the range of r_s is reduced from $[0, 2]$ in (24) to $[0, 1.993]$ in (26). When γ_s is higher than 8 dB, there is no longer any difference between the formulations in (24) and (25). As a result, we can expect that the transformed convex formulation (25) would obtain the same optimal solution as before the variable transformation in most cases. The possibility of obtaining sub-optimal solutions in some low SNR cases is a trade-off in order to formulate the problem as a convex optimization problem.

In a WLAN where all the wireless stations communicate with the AP directly, the AP can measure the SNR (γ_s) of each link and use this information to solve the persistent probability p_s at the MAC layer, and the multiplexing gain r_s at the MIMO physical layer. The resulting r_s and p_s values can be sent to each wireless station via piggyback on the control frames. Each station will then tune its operating parameters accordingly. Furthermore, the AP can adjust the parameter β in the network utility function to adaptively tune the tradeoff between enhancing the throughput of best-effort traffic and the reliability of real-time flows. The NUM formulation also faces the problem of non-feasibility when some link SNRs are too low. We may either reduce the QoS demand or disassociating weak stations from the network to reach a feasible solution.

2) *Distributed Scheme NUM-D*: The *NUM-O* problem proposed in (24) is a centralized scheme, where the AP acts as the central controller and distributes the control information to each wireless station. This may suffer from a single-point failure. An alternative would be a fully distributed algorithm, where each wireless station can decide its own operation parameters based on the locally available information and limited message exchanges. Since problem (25) is convex, the dual decomposition approach can be used to obtain the distributed solution. By relaxing the first two constraints, the Lagrangian function for problem (25) is:

$$\begin{aligned} L(\mathbf{x}', \mathbf{y}, \mathbf{r}, \mathbf{p}', \mathbf{p}'', \boldsymbol{\lambda}, \boldsymbol{\mu}) &= \sum_{i \in \mathcal{N}_1} \beta U_1'(x'_i, y_i) + \sum_{j \in \mathcal{N}_2} (1 - \beta) U_2(y_j) \\ &+ \sum_{s \in \mathcal{N}} \lambda_s (\log k_c + \log r_s + \log(\log \gamma_s) + p'_s \\ &+ \sum_{k \in \mathcal{N} \setminus \{s\}} p''_k - x'_s) \\ &+ \sum_{s \in \mathcal{N}} \mu_s \left(1 - y_s - k_p \gamma_s^{-(M_T - r_s)(M_R - r_s)} \right) \end{aligned} \quad (28)$$

The Lagrange dual function is:

$$\Phi(\boldsymbol{\lambda}, \boldsymbol{\mu}) = \max_{\mathbf{x}', \mathbf{y}, \mathbf{r}, \mathbf{p}', \mathbf{p}''} L(\mathbf{x}', \mathbf{y}, \mathbf{r}, \mathbf{p}', \mathbf{p}'', \boldsymbol{\lambda}, \boldsymbol{\mu}) \quad (29)$$

where $\mathbf{x}', \mathbf{y}, \mathbf{r}, \mathbf{p}', \mathbf{p}''$ are subject to the third to the ninth constraints of (25).

The dual optimization problem can be formulated as:

$$\min \Phi(\boldsymbol{\lambda}, \boldsymbol{\mu}), \quad \text{subject to } \boldsymbol{\lambda} \succeq \mathbf{0}, \text{ and } \boldsymbol{\mu} \succeq \mathbf{0}, \quad (30)$$

which is optimized over $\boldsymbol{\lambda}$ and $\boldsymbol{\mu}$.

Due to the separability of variables in (28), the problem can be decomposed into two sub-problems. The maximization of the Lagrangian over $\mathbf{x}', \mathbf{y}, \mathbf{r}, \mathbf{p}', \mathbf{p}''$ can be conducted in parallel at the application layer for the target throughput $\mathbf{x}'$ and reliability $\mathbf{y}$:

$$\begin{aligned} \max \quad & \sum_{i \in \mathcal{N}_1} \beta U_1'(x'_i, y_i) + \sum_{j \in \mathcal{N}_2} (1 - \beta) U_2(y_j) \\ & - \sum_{s \in \mathcal{N}} (\lambda_s x'_s + \mu_s y_s) \\ \text{subject to} \quad & \log \tilde{x}_1 \leq x'_i \leq \log \hat{x}, \quad \forall i \in \mathcal{N}_1 \\ & \log R \leq x'_j \leq \log \hat{x}, \quad \forall j \in \mathcal{N}_2 \\ & \tilde{y}_1 \leq y_i \leq 1, \quad \forall i \in \mathcal{N}_1 \\ & Q \leq y_j \leq 1, \quad \forall j \in \mathcal{N}_2 \end{aligned} \quad (31)$$

which is optimized over $\mathbf{x}'$ and $\mathbf{y}$.

And, on the MAC/PHY layers for the transmission probability $\mathbf{p}$ and MIMO diversity gain $\mathbf{r}$:

$$\begin{aligned} \max \quad & \sum_{s \in \mathcal{N}} [\lambda_s (\log r_s + p'_s + \sum_{k \in \mathcal{N} \setminus \{s\}} p''_k) \\ & - \mu_s k_p \gamma_s^{-(M_T - r_s)(M_R - r_s)}] \\ \text{subject to} \quad & e^{p'_s} + e^{p''_s} \leq 1, \quad \forall s \in \mathcal{N} \\ & p'_s, p''_s \leq 0, \quad \forall s \in \mathcal{N} \\ & 0 \leq r_s \leq \Delta, \quad \forall s \in \mathcal{N} \end{aligned} \quad (32)$$

which is optimized over $\mathbf{p}$ and $\mathbf{r}$.

The above problem can be separately solved at each wireless station locally. For $i \in \mathcal{N}_1$ with AC_1 traffic, it solves the following problem to obtain its target x'_i and y_i values:

$$\begin{aligned} \max \quad & \beta U_1'(x'_i, y_i) - (\lambda_i x'_i + \mu_i y_i) \\ \text{subject to} \quad & \log \tilde{x}_1 \leq x'_i \leq \log \hat{x}, \\ & \tilde{y}_1 \leq y_i \leq 1, \end{aligned} \quad (33)$$

which is optimized over x'_i and y_i .

For station $j \in \mathcal{N}_2$ with AC_2 traffic, its target x'_j and y_j values can be calculated from:

$$\begin{aligned} \max \quad & (1 - \beta) U_2(y_j) - (\lambda_j x'_j + \mu_j y_j) \\ \text{subject to} \quad & \log R \leq x'_j \leq \log \hat{x}, \\ & Q \leq y_j \leq 1, \end{aligned} \quad (34)$$

which is optimized over x'_j and y_j .

For station $s \in \mathcal{N}$, the MIMO diversity gain $\mathbf{r}$ at the PHY layer can be calculated from:

$$\begin{aligned} \max \quad & \lambda_s \log r_s - \mu_s k_p \gamma_s^{-(M_T - r_s)(M_R - r_s)} \\ \text{subject to} \quad & 0 \leq r_s \leq \Delta. \end{aligned} \quad (35)$$

From (32), since $\sum_{s \in \mathcal{N}} \lambda_s (p'_s + \sum_{k \in \mathcal{N} \setminus \{s\}} p''_k) = \sum_{s \in \mathcal{N}} (\lambda_s p'_s + \sum_{k \in \mathcal{N} \setminus \{s\}} \lambda_k p''_s)$, the transmission probability $\mathbf{p}$ can be solved at each wireless station s by:

$$\begin{aligned} \max \quad & \lambda_s p'_s + \sum_{k \in \mathcal{N} \setminus \{s\}} \lambda_k p''_s \\ \text{subject to} \quad & e^{p'_s} + e^{p''_s} \leq 1, \\ & p'_s, p''_s \leq 0. \end{aligned} \quad (36)$$

With the subgradient projection algorithm, λ_s and μ_s can be updated at each station as follows:

$$\lambda_s(t+1) = [\lambda_s(t) - \delta(t)(\log r_s + p'_s + \sum_{k \in \mathcal{N} \setminus \{s\}} p''_k + \log k_c + \log \log \gamma_s - x'_s)]^+, \quad (37)$$

$$\mu_s(t+1) = [\mu_s(t) - \delta(t)(1 - y_s - k_p \gamma_s^{-(M_T - r_s)(M_R - r_s)})]^+, \quad (38)$$

where $[x]^+ = \max(x, 0)$, and $\delta(t)$ is the diminishing step size [28] (e.g., $\delta(t) = 1/(1+t)$). By taking the advantage of the broadcast nature of the wireless transmission, the values of λ and p which are required in each iteration can be piggybacked over a broadcast frame by each station. Thus, it introduces limited overhead in the network. Another advantage of the distributed solution is that the computation complexity is reduced compared with the centralized scheme. This will benefit a mobile node which would save its CPU utilization and battery consumption. Furthermore, when the framework is extended into multiple hops, the distributed solution would introduce more substantial performance gains than the central computation. Extension of the single-hop WLAN to multiple hops is under our further study. The distributed algorithm (33) to (38) runs at each wireless station s by calculating its target throughput x_s , reliability requirement y_s , MIMO diversity gain r_s , and transmission probability p_s . The r_s and p_s results can then be used to adjust the PHY/MAC operation parameters.

C. NUM-S: Utility-Maximization with Separated PHY/MAC Layers

For performance analysis, we propose a simplified scheme in which the persistent probabilities at the MAC layer and the multiplexing-diversity tradeoff scheme at the physical layer are determined separately. We call this scheme *NUM-S*, and use it as a baseline for performance comparison in Section IV.

At the MAC layer, it is shown that under identical traffic and data rate, the network throughput is maximized with each node transmitting with persistent probability [29]:

$$p_s = 1/N, \quad s \in \mathcal{N}, \quad (39)$$

where $N = |\mathcal{N}|$. If p_s is selected from (39), then the MIMO multiplexing-diversity tradeoff at the physical layer for each station becomes independent of each other and can be computed as follows: At the physical layer, the AC_2 station j can calculate its required level of MIMO multiplexing gain for providing the CBR data rate R from (18):

$$r_j = \frac{RN^N}{k_c \log \gamma_j (N-1)^{N-1}}, \quad j \in \mathcal{N}_2. \quad (40)$$

The value r_j is the minimum multiplexing gain required for sustaining the data rate R , which leads to the corresponding maximum diversity gain from (2) because d_j is a strictly decreasing function of r_j . This maximum diversity gain d_j in turn provides the maximum reliability y_j available for station j as from (5). Because the utility function (22) is strictly increasing with y_j , this multiplexing-diversity tradeoff maximizes the utility for AC_2 stations.

TABLE II
SIMULATION PARAMETERS

Basic Rate	10 Mbps
Maximum Data Rate	80 Mbps
DSSS PLCP Preamble and Header	192 bits
MAC Header	192 bits
FCS (Frame Check Sequence)	32 bits
ACK Frame Size (include Headers)	304 bits
Data Packet Size	1000 bytes
Time Slot	9 μs
SIFS	10 μs
AIFS	28 μs
Maximum Number of Retransmissions	5

For the AC_1 stations, maximizing $U_1(xy)$ in (27) is equivalent to maximizing xy because it is strictly increasing with xy . We can solve the optimal multiplexing gain r_i for each AC_1 station $i \in \mathcal{N}_1$ with the following simple constrained maximization problem:

$$\begin{aligned} \max_{r_i} \quad & k_c r_i \log(\gamma_i) \frac{(N-1)^{N-1}}{N^N} \left(1 - k_p \gamma_i^{-d(r_i)}\right), \\ \text{subject to} \quad & \tilde{x}_1 \leq k_c r_i \log(\gamma_i) \frac{(N-1)^{N-1}}{N^N} \leq \hat{x}, \\ & \tilde{y}_1 \leq 1 - k_p \gamma_i^{-d(r_i)} \leq 1, \\ & d(r_i) = (M_T - r_i)(M_R - r_i), \\ & 0 \leq r_i \leq \min(M_T, M_R). \end{aligned} \quad (41)$$

The solution of problem (41) provides each AC_1 station with its MIMO multiplexing gain r_i , and the transmission reliability y_i can be subsequently calculated from (5). With the reliability results from AC_2 stations, we can obtain the network utility from (25) to compare with the *NUM-D* scheme.

IV. PERFORMANCE EVALUATION

A. Results for 802.11e EDCA

We carry out network simulations by using the ns-2 [30] simulator to study the effectiveness of the cross-layer optimization framework proposed in this paper. The simulation parameters are shown in Table II. We consider a WLAN with 10 wireless stations. Five of them have AC_1 traffic, and five of them have AC_2 traffic. To effectively study the traffic differentiation effects on our proposed schemes, we use the same SNR values for each pair of AC_1 and AC_2 stations. That is $\gamma_i = \gamma_{i+5}$ (for $i = 1, \dots, 5$). Each γ_i is a Gaussian distributed random variable with a mean value of $\gamma_m = 10$ dB, and a variance of $\gamma_v = 5$. To avoid obtaining a too low SNR from the Gaussian random number generator, which will likely lead to no feasible solution for the optimization problem, we set a lower SNR bound of 3 dB. This setup tries to simulate a WLAN with wireless stations randomly located within certain distances from the AP. Other assumptions such as uniformly distributed SNRs have also been tested, and do not seem to have a major impact on the performance comparisons. In fact, the *U-MAC* and *D-MAC* models do not make any assumptions on the SNR's distributions. And our tests also show that similar performance trends are observed under differently simulated SNRs. Thus, only results from the Gaussian distributed SNRs are presented.

(a) Average throughput performance between U-MAC, D-MAC, and 802.11e.

(b) Average delay performance between U-MAC, D-MAC, and 802.11e.

Fig. 1. Performance of U-MAC and D-MAC versus β .

For *U-MAC* and *D-MAC*, the following parameters are used: $k_c = 20$ MHz, $k_p = 0.15$, $M_T = 2$, $M_R = 3$, $\tilde{W}_s = \tilde{W}_a = 7$, $\hat{W}_s = \hat{W}_a = 1023$, $\alpha = 1.1$, $\tilde{y}_1 = 0.7$, $\tilde{y}_2 = 0.85$, and $\Gamma = 1$. With a maximum of five retransmissions, the maximum contention window size is set to be $2^5 = 32$ times the minimum contention window size. The resulting MIMO multiplexing gain r and contention window size CW from the solution of (16) or (17) are used in the ns-2 simulator to assign the proper physical and MAC operating parameters. We vary β from 0.1 to 0.5 to study the effectiveness of the traffic differentiation effect of our proposed schemes. Smaller β improves the higher priority AC_2 's performance, but at a price of decreasing performance of AC_1 . A desired tradeoff may be obtained by assigning the appropriate β by the network administrator.

We compare the proposed adaptive cross-layer schemes *U-MAC* and *D-MAC* with the original 802.11e MAC. We look at the following three main performance metrics: the traffic's throughput, delay and the network's utility. The throughput is calculated as the end-to-end network throughput above the MAC layer, which is the number of bits transmitted in the transport layer protocol data unit (PDU) divided by time. For the original 802.11e MAC, the $\tilde{W}_1$ and $\tilde{W}_2$ are chosen as 7 and 31, respectively, according to the standard specifications. In order to have a meaningful performance comparison, we

Fig. 2. Network utility of U-MAC and D-MAC versus β .

also use MIMO links with the 802.11e MAC. The multiplexing gain r_s of wireless station s is chosen without the cross-layer optimization as done in the *U-MAC* and *D-MAC* schemes. Its r_s is chosen by (5) such that wireless station s would achieve a link reliability of 0.9 with its channel SNR γ_s . We will study the effectiveness of the tuning β on the traffic QoS differentiation. The network total utility is used to evaluate the effectiveness of the schemes in achieving better utility values, which corresponds to a higher network revenue and better user QoS satisfactions.

Fig. 1(a) shows the aggregated throughput of each AC. Because of the static nature of the 802.11e MAC scheme, its performance values do not change with β , and are drawn as a horizontal line in the figure to be used as a comparison baseline. The medium access delay is shown in Fig. 1(b). An increase in β decreases the priority differentiation between the two ACs. When β reaches 0.5, AC_1 and AC_2 reach equal priority and have comparable performances.

The network utility is shown in Fig. 2. Although the 802.11e MAC does not consider β , its x_s , y_s values are also substituted into (15) to calculate the network utility under different β . Fig. 2 shows that the *U-MAC* and *D-MAC* maintain a relatively high network utility, while the 802.11e is not adaptive to different β adjustments and its network utility decreases sharply when the utility function demands less traffic differentiation by increasing the β value.

Simulation results show that the adaptive *U-MAC* and *D-MAC* schemes have good flexibility in adapting to the network's different assignment of weights to the two access categories. They also consistently outperform the original 802.11e MAC in every performance measure because they jointly adapt the minimum contention window size values and the MIMO coding schemes. These results verify that those simplifying assumptions that we made to formulate the computationally efficient NUM problem in Section II are reasonable and sound.

We can also observe that the *U-MAC* slightly outperforms the *D-MAC*, even though *D-MAC* allows the extra flexibility of letting each station have its own $\tilde{W}_s$ parameter. The cause for this is from the coarse approximation we made in the throughput model for *D-MAC*, while the *U-MAC* model is more accurate. However, an insight that we can gain from these simulation experiments is that restricting each access

TABLE III
NUM SOLUTION FOR THE U-MAC SCHEME.

		AC_1					AC_2				
Station s		1	2	3	4	5	6	7	8	9	10
β	γ_s	6 dB	7 dB	8 dB	9 dB	10 dB	6 dB	7 dB	8 dB	9 dB	10 dB
0.1	W_s	220					29				
0.2	W_s	120					33				
0.3	W_s	84					38				
0.4	W_s	65					45				
0.5	W_s	53					53				
0.1	r_s	1.552	1.522	1.496	1.470	1.442	1.549	1.528	1.502	1.476	1.449
0.2	r_s	1.554	1.524	1.497	1.471	1.444	1.549	1.528	1.501	1.475	1.449
0.3	r_s	1.555	1.525	1.498	1.472	1.445	1.549	1.528	1.501	1.475	1.448
0.4	r_s	1.556	1.526	1.499	1.473	1.446	1.549	1.527	1.500	1.474	1.447
0.5	r_s	1.557	1.527	1.500	1.474	1.447	1.549	1.526	1.500	1.474	1.447

TABLE IV
NUM SOLUTION FOR THE D-MAC SCHEME.

		AC_1					AC_2				
Station s		1	2	3	4	5	6	7	8	9	10
β	γ_s	6 dB	7 dB	8 dB	9 dB	10 dB	6 dB	7 dB	8 dB	9 dB	10 dB
0.1	W_s	36	33	31	29	27	7	7	7	7	7
0.2	W_s	23	22	20	19	18	7	7	7	7	7
0.3	W_s	17	16	15	14	13	8	8	7	7	7
0.4	W_s	14	13	12	11	10	10	9	8	8	7
0.5	W_s	11	10	10	9	9	11	10	10	9	9
0.1	r_s	1.632	1.631	1.632	1.636	1.640	1.539	1.528	1.523	1.521	1.522
0.2	r_s	1.562	1.569	1.576	1.583	1.591	1.538	1.540	1.533	1.531	1.531
0.3	r_s	1.538	1.546	1.554	1.563	1.571	1.528	1.536	1.545	1.547	1.546
0.4	r_s	1.530	1.539	1.548	1.557	1.565	1.526	1.535	1.544	1.553	1.561
0.5	r_s	1.528	1.537	1.546	1.554	1.563	1.528	1.537	1.546	1.554	1.563

category to have uniform minimum contention window sizes may be sufficient to provide good performance gain in the MIMO-enabled cross layer design framework. We may be able to improve the performance of *D-MAC* by further refining its throughput model.

To have a better understanding of the system behavior near the optimal values, we present a set of results of the system variables from the NUM framework in Tables III and IV. Ten wireless stations are also used in the tests. The link SNR values $\gamma_i = \gamma_{i+5}$ (for $i = 1, \dots, 5$) are set at increasing values (from 6 dB to 10 dB) instead of random numbers so that it is easier to observe the behavior of the system variables. β is increased from 0.1 to 0.5. From the tables, we can see that the difference of the diversity gain and contention window size of the two AC 's stations diminishes when β approaches 0.5. In previous simulation tests, the *D-MAC* slightly under-performs *U-MAC*. From these two tables, we can see that the *D-MAC* tends to use a smaller contention window size than the *U-MAC* model, which is likely the cause for the performance loss. A more accurate throughput model for *D-MAC* will be needed for improving this performance gap.

B. Results for Slotted Aloha MAC

The slotted Aloha schemes *NUM-D* and *NUM-S* are studied with numerical tests in Matlab. The following parameters are used: $\tilde{x} = 0.01$ Mbps, $\hat{\gamma} = 30$ dB, $Q = 0.85$, and the other parameters use the same values as in Section IV-A. The stopping criteria for *NUM-D* is that $|\lambda_s(t+1) - \lambda_s(t)|$ and $|\mu_s(t+1) - \mu_s(t)|$ are less than 10^{-6} for all s .

Fig. 3. The tradeoff between throughput and reliability for slotted Aloha.

1) *Effect of β on the Network Utility Function:* First, we examine the effectiveness of the network utility function (23) in determining the tradeoff between the throughput of AC_1 and the reliability of AC_2 . We vary the parameter β from 0.6 to 1 with a step size of 0.05, and solve problem (25). We use the Gaussian distributed random variable with a mean value of γ_m and a variance of γ_v to generate the SNR values in simulations. The results for $N_1 = N_2 = 5$, $\gamma_m = 8$ dB, $\gamma_v = 0.5\gamma_m$, and varying R are shown in Fig. 3. The throughput is calculated from (18) which is the throughput for transmitting the MAC layer protocol data unit with MAC frame headers. We can see that for a smaller β , the throughput in AC_1 is given lower priority, but the network achieves higher reliability for the AC_2 traffic. As β

(a) Network utility versus the number of wireless stations.

(a) Network utility versus the average SNR.

(b) Average throughput performance for best-effort traffic.

(b) Average throughput performance for best-effort traffic.

(c) Average reliability for real-time traffic.

(c) Average reliability for real-time traffic.

Fig. 4. Slotted Aloha under NUM-D and NUM-S with different number of wireless stations.

increases, the throughput in AC_1 significantly increases at the price of decreasing reliability on AC_2 traffic. The area below each curve is effectively the achievable throughput-reliability region for a specified R . When R increases, this region shrinks because more resources have to be allocated to guarantee the higher throughput requirement from the AC_2 traffic. Fig. 3 shows that the utility function (23) has great flexibility in adapting different user QoS requirements by adjusting the parameter β . If the network operators can generate higher revenues by providing high reliability for AC_2 traffic, they may tend to choose a smaller β value. In the following tests, we choose $\beta = 0.85$.

Fig. 5. Slotted Aloha under NUM-D and NUM-S with different SNR.

2) *Performance under Different Number of Stations:* In this experiment, γ_m is fixed at 8 dB, and $\gamma_v = 0.5\gamma_m$. We vary the number of stations in each AC from 1 to 5. R is set at 1.5 Mbps. The resulting network utility, the throughput AC_1 and reliability performance in AC_2 are shown in Figs. 4(a) to 4(c). When the number of stations is small, the NUM-D scheme achieves much higher AC_1 throughput than NUM-S. When the number of stations increases, the performance gain on AC_1 's throughput by NUM-D diminishes. But NUM-D is able to maintain the AC_2 's reliability above 95%, while NUM-S's reliability performance significantly deteriorates. Overall, the network utility achieved by NUM-D is consistently higher

TABLE V
SOLUTION FOR THE NUM-D SCHEME.

Station s	AC_1					AC_2				
	1	2	3	4	5	6	7	8	9	10
γ_s	6 dB	7 dB	8 dB	9 dB	10 dB	6 dB	7 dB	8 dB	9 dB	10 dB
p_s	0.090	0.089	0.089	0.088	0.087	0.138	0.122	0.109	0.099	0.090
r_s	1.562	1.575	1.587	1.599	1.610	1.124	1.149	1.173	1.195	1.216
x_s (Mbps)	0.864	0.969	1.074	1.179	1.283	1.000	1.000	1.000	1.000	1.000
y_s	0.843	0.857	0.869	0.879	0.888	0.973	0.980	0.982	0.986	0.989
λ_s	0.085	0.085	0.084	0.083	0.082	0.130	0.115	0.103	0.093	0.085
μ_s	0.102	0.099	0.097	0.094	0.092	0.943	0.937	0.934	0.930	0.927

than *NUM-S*.

3) *Performance under Different SNRs*: In this experiment, N_1 and N_2 are set to 5. The network average γ_m varies from 6 dB to 16 dB, $\gamma_v = 0.5\gamma_m$. R is equal to 1.0 Mbps. Figs. 5(a) to 5(c) show the network utility, AC_1 's throughput and AC_2 's reliability achieved with these two schemes. Results show that in the lower SNR region, *NUM-D* sacrifices a portion of AC_1 's throughput to achieve consistently high reliability for AC_2 , while at the higher SNR region, *NUM-D* achieves significantly higher throughput than *NUM-S* and also maintains AC_2 's reliability greater than 99%. As a result, it successfully achieves a good balance between throughput for best-effort traffic and reliability for real-time traffic and attains higher network utility than the *NUM-S* scheme.

To study the detailed system variable behavior at the optimal solution, we also present a set of results with pre-determined SNR values in Table V. We can see that the solutions provide the required 1 Mbps throughput for the AC_2 traffic with good reliability. The best-effort AC_1 traffic tends to use higher a multiplexing gain r_s to achieve a higher data rate. The stations with higher SNR links can use a higher multiplexing gain and lower transmission probability to achieve the required link reliability and throughput.

The above results show that the cross-layer network utility maximization formulation of (24) successfully balances between the QoS requirements of the two access categories by jointly adapting MAC and MIMO physical layer parameters.

V. CONCLUSIONS

This paper proposed a MAC/PHY cross-layer design with network utility maximization in a WLAN with multiple classes of traffic. Two types of MAC protocol are considered. For the CSMA/CA-based 802.11e EDCA MAC, the minimum contention window size at the MAC layer is jointly optimized with the multiplexing-diversity gain tradeoff at the physical layer with MIMO antennas. The utility-based cross-layer design is shown to be flexible in adjusting the system performance in regard to QoS tradeoff for different access categories of traffic. We further analyzed the slotted Aloha MAC using the NUM approach as well, and were able to derive distributed solutions with variable transformation and dual decomposition of the original NUM problem. Simulation results are presented for both MAC designs, which show the effectiveness in system performance improvement. Future work will consider extending the existing framework to a

multi-hop scenario and further extending the CSMA/CA MAC to work in a distributed manner.

APPENDIX

A. Proof of the concavity of the utility function in (25)

For $\alpha > 1$, we define the constants C_1 and C_2 as follows:

$$C_1 = \frac{1}{(\hat{x})^{1-\alpha} - (\hat{x}_1\hat{y}_1)^{1-\alpha}}$$

$$C_2 = \frac{1}{1 - Q^{1-\alpha}}$$

It is easy to see that $C_1 < 0$ and $C_2 < 0$, because $t^{1-\alpha}$ is a strictly decreasing function of t for $\alpha > 1$. As a result, $C_2 y^{1-\alpha}$ is a concave function of y for $\alpha > 1$. Thus, $U_2(y)$ is a concave function.

For $U_1'(x', y)$, the Hessian matrix of $C_1(e^{x'}y)^{1-\alpha}$ is:

$$\mathbf{H} = \nabla^2 C_1(e^{x'}y)^{1-\alpha} = C_1 e^{(1-\alpha)x'} \times \begin{bmatrix} (1-\alpha)^2 y^{1-\alpha} & (1-\alpha)^2 y^{-\alpha} \\ (1-\alpha)^2 y^{-\alpha} & -\alpha(1-\alpha)y^{-\alpha-1} \end{bmatrix} \quad (42)$$

For any non-zero vector $\mathbf{z} = [z_1 \ z_2]$ and $\alpha > 1$, we have:

$$\mathbf{zH}\mathbf{z}^T = C_1(1-\alpha)e^{(1-\alpha)x'}y^{-\alpha-1}[(1-\alpha)(yz_1 + z_2)^2 - z_2^2] < 0 \quad (43)$$

which shows that $\mathbf{H}$ is negative definite. As a result, the utility function $U_1'(x', y)$ is a concave function of $\{x', y\}$. ■

B. Proof of convexity of the constraints in (25)

For a convex optimization problem, its equality constraints should be affine, and the function $f(x)$ in the inequality constraint $f(x) \leq 0$ should be convex.

It is easy to see that the first constraint in (25) is affine. For the second constraint, in order for the function $w(r_s) = \gamma_s^{-(M_T-r_s)(M_R-r_s)}$ to be convex, it is required that:

$$\nabla^2 w(r_s) = \gamma_s^{-(M_T-r_s)(M_R-r_s)}[(M_T + M_R - 2r_s)^2 \ln \gamma_s - 2] \ln \gamma_s \geq 0. \quad (44)$$

This gives an upper bound of r_s , which is reflected in (26).

The third constraint is relaxed from the equality constraint ($e^{p'_s} + e^{p''_s} = 1$) to an inequality constraint. The main concern is that a non-linear equality constraint makes the problem non-convex. With this relaxation to inequality constraint, the problem becomes convex. Intuitively, this relaxation is reasonable. Suppose that $e^{p'_s} + e^{p''_s}$ is strictly less than 1, we can increase

p'_s or p''_s to reach the upper limit 1. An increase in p'_s or p''_s will lead to relaxing the first constraint, which in turn may lead to higher x'_s , resulting in better network utility. As a result, we may expect that this upper bound of 1 is always tight. Thus, problem (25) is a convex optimization problem over variables $\{\mathbf{x}', \mathbf{y}, \mathbf{r}, \mathbf{p}', \mathbf{p}''\}$. ■

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