QoS, Channel and Energy-Aware Packet Scheduling over Multiple Channels

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Abstract—In this letter, we extend the study from our previous work in [1]. First, we extend physical layer resource allocation problem to a packet based transmission scheme. The proposed packet assignment improves the implementation robustness as it allows for consideration of coded modulation schemes while still ensuring energy efficient transmission as with our previous work. Secondly, we study the impact of channel partition size selection on system performance and complexity.

Index Terms—Quality of service, MIMO, scheduling, crosslayer.

I. INTRODUCTION

MPROVING energy efficiency and throughput are in general two contrasting goals. This problem is further compounded when the need arises to satisfy various quality of service (QoS) demands associated with different types of data traffic such as streaming video or voice over IP.

In our previous work [1] we proposed an energy-aware method to adapt transmission power to efficiently schedule traffic while meeting QoS constraints. In this letter we extend on our previous work which employed bit-level resource allocation, *i.e.*, packets were segmented and transmitted across different eigenchannels of the multiple-input, multiple-output (MIMO) channel downlink. By considering packet-level resource allocation, we can consider both the use of coded transmission modes as well as applying this framework to a more general multiple channel system. Further, we study the tradeoff of channel partitioning on complexity and power performance.

The remainder of this letter is organized as follows. Section II briefly outlines the media access control (MAC) and physical (PHY) layer models of the downlink system. In Section III we detail the scheduler design, while in Section IV formulate the problem using general optimization framework. Selected results and the impact of channel partitioning are studied in Section V and brief conclusions are drawn in Section VI.

II. SYSTEM MODEL

The multi-queue, multi-channel downlink system is composed of a base station transmitting traffic to a single subscriber station as shown in Fig. 1 of [1]. Both the MAC and PHY models are described in detail in [1] and summarized briefly here.

Frame n Frame n+1 Frame n+2 Frame n+3 Frame n+4 T_f T_f T_f STA2 STA2 STA2 STA2 STA3 STA3 STA4 STA1 STA4 STA4 STA4 STA1 STA1

Fig. 1. Frame timing layout.

There are K traffic classes using independent FIFO buffers with parameter set $\{\mathcal{D}_i, L_i, \overline{\lambda}_i, B_i, \delta_i\}$ describing the maximum tolerable average delay, packet size, average arrival rate, buffer size and maximum tolerable packet loss rate respectively. The tolerable loss rate can further be expressed by its components: $\delta_i = 1 - (1 - P_{d,i})(1 - P_{l,i})$; where $P_{d,i}$ and $P_{l,i}$ denote the probability of packets dropped entering the queue and packets dropped due to channel errors respectively. During each frame, a number of packets are taken from each queue and transmitted to the subscriber station. The scheduling algorithm employed is QoS-aware and formulates scheduling decisions based on the channel state information (CSI) from the subscribing station and information about its instantaneous buffer levels and individual traffic class QoS requirements.

The scheduling time horizon is divided into a number of frames as shown in Fig. 1. Each frame has a duration of T_f seconds and has a fixed number of symbols of duration T_s seconds in each subchannel. Based on the adaptive modulation and coding (AMC) mode chosen, each subchannel can carry a given number of bits. From frame to frame, the evolution of each buffer can be described by the number of departures $c_i(n)$, the number of arrivals $A_i(n)$ and the previous buffer occupancy level $u_i(n)$. An example frame allocation is shown in Fig. 1.

The base station and receiver are both equipped with multiple antennas. There are M_T antennas at the base station and M_R antennas at the receiving station. The system employs singular value decomposition (SVD) eigenbeamforming. In general a MIMO SVD system allows up to $M = \min\{M_T, M_R\}$ parallel subchannels for transmission. Measurement campaigns however have suggested [2], [3] that the number of non-zero eigenvalues in general is less than the minimum number of antennas (i.e., $L \leq \min\{M_T, M_R\}$). Such channels are known as sparse, and in fact can be modeled using a well-described geometric approach [4] to which the underlying time-varying parameters have been well-studied [5].



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From [5], we know the ℓ^{th} unordered channel eigenvalue has a known probability density function (PDF) of¹

$$f_{\Lambda_{\ell}}(\lambda_{\ell}) = \frac{1}{M_R M_T P_{\ell}} \exp\left(-\frac{\lambda_{\ell}}{M_R M_T P_{\ell}}\right)$$
(1)

where P_{ℓ} is the relative power of that contributing cluster (described in [4]) such that $\sum_{\ell=1}^{L} P_{\ell} = 1$. The equivalent SNR of each subchannel of the SVD system for a reference SNR γ_0 is then [6]

$$\gamma_{\ell} = \frac{\gamma_0}{M_T} \lambda_{\ell} \tag{2}$$

Finally, the density function of the channel at a reference SNR γ_0 is simply

$$f_{\Gamma_{\ell}}(\gamma_{\ell}) = \frac{1}{\gamma_0 M_R P_{\ell}} \exp\left(-\frac{\gamma_{\ell}}{\gamma_0 M_R P_{\ell}}\right)$$
(3)

While each time-varying subchannel SNR can be described by the distribution in (3), recent cross-layer design techniques [7]–[9] partition the channel into a finite number of states [10] in scheduler design which reduces decision complexity.

In the case of multiple parallel subchannels, the overall state of the channel can be described by jointly considering the state of all parallel subchannels. Denoting \mathcal{J}_{ℓ} as a set of finite states of the ℓ^{th} unordered channel SNR, each j_{ℓ}^{th} subchannel state is bounded by $[\varphi_{\ell,j_{\ell}}, \varphi_{\ell,j_{\ell}+1}]$ where $\varphi_{\ell,1} = 0$ and $\varphi_{\ell,|\mathcal{J}_{\ell}|+1} = \infty$ for each subchannel ℓ . Here $|\cdot|$ denotes the size of a set (or the number of partitions for a given subchannel ℓ). Further, we can express \mathcal{J} (or the joint channel state) as

$$\mathcal{J} = \mathcal{J}_1 \times \dots \times \mathcal{J}_L \tag{4}$$

There are a number of partitioning methods discussed in the literature [7], [10]. Further research has shown [9] that properly designed channel partitioning thresholds can offer another degree of design freedom in adaptive transmission design, however we do not focus on that here². Here, we employ an equal probability method such that the bounds are chosen to satisfy

$$\int_{\varphi_{\ell,j_{\ell}}}^{\varphi_{\ell,j_{\ell}+1}} f_{\Gamma_{\ell}}(r) dr = \frac{1}{|\mathcal{J}_{\ell}|}, \qquad j_{\ell} = 1, 2, \dots, |\mathcal{J}_{\ell}| \quad \text{and} \qquad (5)$$

where for a given number of partitions $|\mathcal{J}_{\ell}|$ and for a subchannel SNR distribution in (3), the above can be easily found as

$$\varphi_{\ell,j_{\ell}+1} = -\gamma_0 M_R P_{\ell} \ln\left(1 - \frac{j_{\ell}}{|\mathcal{J}_{\ell}|}\right), j_{\ell} = 1, \dots, |\mathcal{J}_{\ell}| - 1 \quad (6)$$

The power level required to maintain a given loss rate on the channel, $P_{l,i}$, will depend on both the channel states described above, the subchannel of interest, the packet size and chosen AMC mode in that subchannel of interest. By using packet level allocation, packet error rates for coded transmissions can be easily accounted for using known analytical expressions.

¹While this letter focuses on the illustrative case of sparse MIMO channels, extensions are trivial for any MIMO model with known eigenvalue distribution. As a result the presented framework can be applied in a general MIMO multiple channel scenario.

Here, we use the block outage probability (BLOP) derived in [11] to model the instantaneous packet error rate of the subchannel which is given as

$$PER(\gamma, k_{\ell}, L_i) \approx Q\left(\frac{\log(1+\gamma) - \log(2)k_{\ell}}{\sqrt{\frac{2k_{\ell}}{L_i}\frac{\gamma}{1+\gamma}}}\right)$$
(7)

where γ is a given SNR level, k_{ℓ} is the spectral efficiency (number of bits per symbol) and $Q(\cdot)$ is the well-known Q-function. The factor $\log(2)$ follows from [11] in that we measure spectral efficiency in bits per symbol.

Therefore the loss rate on the subchannel is given as the average PER over state j_{ℓ} of subchannel ℓ with applied power \mathcal{P} as

$$P_{l,i} = \frac{1}{|\mathcal{J}_{\ell}|} \int_{j_{\ell}}^{j_{\ell}+1} PER(\gamma_{\ell}\mathcal{P}, k_{\ell}, L_i) f_{\Gamma_{\ell}}(\gamma_{\ell}) d\gamma_{\ell}$$
(8)

III. SCHEDULER DESIGN AND FORMULATION

The scheduler has two-stages originally described in [1] where the scheduler allocates a set of MAC rates based on the QoS parameters (*i.e.*, delay, throughput and buffer occupancy levels), and performs power, rate and channel allocation based on the required MAC rate in conjunction with channel CSI. In this letter, we propose a modified algorithm for the power, rate and channel allocation stage, for use in conjunction with the MAC rate assignment stage in [1].

Due to physical transmission limitations, only a small number of packets relative to the queue size can be serviced from the queue during each frame. Let C_i be the set of possible MAC rates (*i.e.*, a set containing the possible quantity of packets that can be serviced from queue *i* during any frame). Subsequently, C can then describe all possible combinations of queue service rates across the set of queues or equivalently as

$$\mathcal{C} = \prod_{i=1}^{K} \mathcal{C}_i \tag{9}$$

Given a set C expressing the exhaustive MAC transmission rates for the MAC layer, each $c \in C = \{c_1, c_2, \ldots, c_K\}$, target channel losses $P_{l,i}$, the set of channel states \mathcal{J} and the set of valid AMC modes \mathcal{M} , the physical layer allocation scheme can be formulated as follows.

First, one can express the channel state and MAC rate assignment state space as $S = C \times J$. For each $s \in S$, the problem is formulated as follows.

To select a set of AMC modes $\mathbf{k}(s) = \{k_{\ell}(s), \forall \ell\}$ and a channel mapping scheme $\bar{X}_{\ell,i}(s), \forall \ell, i$ such that the total average power level selection is minimized. Let $\bar{X}_{\ell,i}(s)$ denote the number of packets from queue *i* to be transmitted in subchannel ℓ while in system state *s* with a transmission power of $P(i, \ell, \mathcal{J}_{\ell}(s), k_{\ell}(s))$, and where $\mathcal{J}_{\ell}(s)$ is the state of subchannel ℓ while in system state *s*. $P(i, \ell, \mathcal{J}_{\ell}(s), k_{\ell}(s))$ is found from solving (8) for \mathcal{P} for a given target channel loss rate $P_{l,i}$. Due to the monotonicity of (7) in γ , \mathcal{P} can be found from (8) using efficient numerical techniques.

²Of Further note, while the number of partitions can impact the scheduler computational complexity as shown later, the method of choosing partition thresholds of the channel does not.

TABLE I Frequently Used Notation

Quantity	Symbol	Quantity	Symbol
Number of traffic streams	K	Subchannel SNR	γ_ℓ
Number of parallel subchannels	L	Spectral efficiency in subchannel ℓ	k_ℓ
Average delay constraint	${\mathcal D}_i$	Subchannel eigenvalue	λ_ℓ
Packet size in bytes	L_i	Relative cluster power	P_ℓ
Average arrival rate	$\bar{\lambda_i}$	Mean SNR of subchannel ℓ in system state s	$\mu_\ell(s)$
Buffer size	B_i	Reference SNR	γ_0
Total average loss constraint	δ_i	MAC rate state-space	${\mathcal C}_i$
Packet dropping probability	$P_{d,i}$	Joint MAC rate state-space	\mathcal{C}
Packet error rate on the channel	$P_{l,i}$	Set of subchannel states	\mathcal{J}_ℓ
Frame duration	T_{f}	Number of packets allocated to subchannel ℓ from stream i	$\bar{X}_{\ell,i}$
Symbol duration	T_s	Packet service rate of queue i during frame n	$c_i(n)$
Frame number	n	Average number of arrivals during frame n	$A_i(n)$
Set of valid AMC modes	\mathcal{M}	Buffer occupancy during frame n	$u_i(n)$

With the above definition, we define the power, channel and AMC allocation optimization (for $s \in S$) subproblem to minimize the average applied transmission power as

$$\bar{P}(s) = \min_{\mathbf{k}(s), \bar{\mathbf{X}}(s)} f(\mathbf{k}(s), \bar{\mathbf{X}}(s))$$
(10)

where

$$f(\mathbf{k}(s), \bar{\mathbf{X}}(s)) = \sum_{i=1}^{K} \sum_{\ell=1}^{L} \sum_{k_{\ell} \in \mathcal{M}}^{M} S_{k_{\ell}, \ell}(s) \cdot P(i, \ell, \mathcal{J}_{\ell}(s), k_{\ell}) \left[\frac{\bar{X}_{\ell, i}(s) L_{i}}{k_{\ell}} \right]$$
(11)

where $\mathbf{k}(s)$ and $\mathbf{X}(s)$ are the vector and matrices containing $k_{\ell}(s), \forall \ell$ and $\bar{X}_{\ell,i}(s), \forall \ell, i$ respectively, $k_{\ell}(s)$ is the spectral efficiency of the chosen AMC mode in bits per symbol and $\lceil \cdot \rceil$ denotes rounding up to the nearest Integer (ceiling function). $S_{k_{\ell}(s),\ell}(s)$ is an indicator function such that $S_{k_{\ell}(s),\ell}(s) = 1$ if a particular AMC mode k_{ℓ} is used for transmission in subchannel ℓ and 0 otherwise. Therefore $k_{\ell}(s) = \{k_{\ell}|S_{k_{\ell},\ell}(s) = 1\}$. Further, we have the following additional constraints

$$\sum_{\ell=1}^{L} \bar{X}_{\ell,i}(s) = c_i(s), \quad \forall i$$
(12)

$$\sum_{i=1}^{K} \bar{X}_{\ell,i}(s) L_i \leq \frac{k_\ell(s)T_f}{T_s}, \quad \forall \ell$$
(13)

$$\sum_{k_{\ell} \in \mathcal{M}} S_{k_{\ell},\ell}(s) = 1, \quad \forall \ell$$
(14)

$$\bar{X}_{\ell,i}(s) \in \mathbb{I}, \qquad \forall i, \ell \tag{15}$$

$$X_{\ell,i}(s) \ge 0, \qquad \forall i, \ell \tag{16}$$

$$S_{k_{\ell},\ell}(s) \in \{0,1\}, \qquad \forall \ell \tag{17}$$

The constraint in (12) ensures that the number of allocated packets for each stream across all subchannels satisfies the MAC requested rate $c_i(s)$, while (13) ensures that the selected AMC mode in each subchannel satisfies the amount of data transmitted over that subchannel. The constraint in (14) enforces that only a single AMC mode can be applied per subchannel during a given time frame. Finally, constraints (15)-(17) enforce Integer/binary restrictions and non-negativity constraints on $\bar{X}_{\ell,i}(s)$ and $S_{k_{\ell},\ell}(s)$.

Solutions to the above problem requires enumeration of all possible combinations of $S_{k_{\ell},\ell}(s)$. This scales as $\mathcal{O}(|\mathcal{M}|^L)$

and results in a large number of possible AMC mode combinations for the optimization routine above. To improve computation efficiency, we take the following two steps. First, the constraints given from (12)-(17) suggest that only a subset of eligible candidate sets for $\{S_{k_{\ell},\ell}(s), \forall \ell\}$ that satisfy the constraints exist. The second is by using subchannel ordering (assigning the highest rate to that of the best quality channel and so on).

A. AMC Selection Space Reduction

The AMC space reduction is as follows. For each $s \in S$, let \mathcal{K} be the set of all AMC mode combinations by enumerating each possible combination of $S_{k_{\ell},\ell}(s)$. Further, let $\mathcal{K}_{inf}(s)$, $\mathcal{K}_{e}(s)$, and $\mathcal{K}_{o}(s)$ be non-overlapping subsets of \mathcal{K} such that

$$\mathcal{K} = \mathcal{K}_{inf}(s) \bigcup \mathcal{K}_e(s) \bigcup \mathcal{K}_o(s) \tag{18}$$

Here $\mathcal{K}_{inf}(s)$ is the set of AMC modes assignments that are infeasible due to insufficient sum rate (fails to satisfy (13))

$$\mathcal{K}_{inf}(s) = \left\{ \mathbf{k} \in \mathcal{K} \left| \sum_{\ell=1}^{L} k_{\ell} \leq \llcorner \epsilon_{inf}(s) \lrcorner, \right. \right\}$$
(19)

where

$$\epsilon_{inf}(s) = \frac{T_s}{T_f} \sum_{i=1}^K c_i(s) L_i \tag{20}$$

with $\lfloor \cdot \rfloor$ denoting rounding down to the next smallest possible AMC mode combination for a given set of allowable spectral efficiencies.

The subset $\mathcal{K}_o(s)$ defines what we refer to as the overfeasible set. This is the subset of AMC mode combinations that likely do not yield the most energy efficient allocation. In general, this set is not unique. By maximizing the size of the overfeasible set, one can minimize the system complexity (i.e., the number of optimization subproblems). We strongly suggest that the largest obtainable overfeasible set without eliminating the most energy efficient allocations is given as

$$\mathcal{K}_o(s) = \left\{ \mathbf{k} \in \mathcal{K} \left| \sum_{\ell=1}^L k_\ell > \lceil \epsilon_o(s) \rceil, \mathbf{k} = \{k_1, \dots, k_L\} \right\}$$
(21)

where

$$\epsilon_o(s) = \frac{T_s}{T_f} \left(L \max\{L_1, \dots, L_K\} + \sum_{i=1}^K c_i(s)L_i \right)$$
 (22)

and $\lceil \cdot \rceil$ denotes rounding up to the next valid AMC mode combination for a given set of allowable spectral efficiencies. The argument for the above is as follows. First, from (19) and by the monotonically increasing nature of (7) in k_{ℓ} , increasing the spectral efficiency of any single channel beyond what is required for channel allocation is inefficient (requires an increase in power to maintain a target PER). Combining this with the granularity of the problem (packet-level assignment granularity), it is possible that the most energy efficient AMC mode selection scheme must be able to assign up to 1 more of the largest granular quantity (largest packet) into any channel ℓ . Finally since $\mathcal{K}_o(s)$, $\mathcal{K}_e(s)$, and $\mathcal{K}_{inf}(s)$ are nonoverlapping sets satisfying (18), one can find $\mathcal{K}_e(s)$ as³

$$\mathcal{K}_e(s) = (\mathcal{K} \setminus \mathcal{K}_{inf}(s)) \setminus \mathcal{K}_o(s) \tag{23}$$

where $\mathcal{K}_e(s)$ is the set possible AMC mode combinations used below.

B. AMC Assignment and Channel Ordering

The channel ordering operation is as follows. First, the mean SNR value of subchannel ℓ in state $\mathcal{J}_{\ell}(s)$ is given by

$$\mu_{\ell}(s) = \int_{\mathcal{J}_{\ell}(s)} \gamma_{\ell} f_{\Gamma_{\ell}}(\gamma_{\ell}) d\gamma_{\ell}$$
(24)

Each $\mathbf{k} \in \mathcal{K}_e(s)$ vector contains the AMC modes for all L subchannels. Let $\bar{\mathbf{k}}$ represent the ordered vector \mathbf{k} such that $\bar{k}_1 \geq \cdots \geq \bar{k}_x \geq \cdots \geq \bar{k}_L$. Let $x = \mathfrak{F}(\ell)$ (with corresponding inverse function $\ell = \mathfrak{F}^{-1}(x)$) return the channel level rank x of subchannel ℓ . A channel level rank of x means that subchannel ℓ has the x^{th} highest mean as given by (24) (*i.e.*, $\mu_{\mathfrak{F}^{-1}(1)}(s) \geq \cdots \geq \mu_{\mathfrak{F}^{-1}(\ell)}(s) \geq \cdots \mu_{\mathfrak{F}^{-1}(L)}(s)$). Each AMC mode \bar{k}_x is mapped to each ordered channel $\mu_{\mathfrak{F}^{-1}(x)}(s)$.

C. Revised Optimization Formulation

One can revise the transmission cost function from (11) to be a function of the allocation matrix $\mathbf{X}(s)$ as

$$f^{\bar{\mathbf{k}}(s)}(\bar{\mathbf{X}}(s)) = \sum_{i=1}^{K} \sum_{\ell=1}^{L} P(i,\ell,\mathcal{J}_{\ell}(s),\bar{k}_{\mathfrak{F}(\ell)}(s)) \\ \cdot \left[\frac{\bar{X}_{\ell,i}(s)L_i}{\bar{k}_{\mathfrak{F}(\ell)}(s)} \right]$$
(25)

where the solution to the optimization problem follows as

$$\bar{P}(c,j) = \bar{P}(s) = \min_{\bar{\mathbf{k}}(s) \in \mathcal{K}_e(s)} \left(\min_{\bar{\mathbf{X}}(s)} f^{\bar{\mathbf{k}}(s)}(\bar{\mathbf{X}}(s)) \right)$$
(26)

For each $s \in S$ (or $j \in J$, $c \in C$), the above can be solved in two stages, which is significantly more efficient than joint optimization. Finally, $\overline{P}(c)$, used in equation (23) of [1], can be found by averaging over all possible subchannel states or as

$$\bar{P}(c) = \frac{1}{|\mathcal{J}|} \sum_{j \in \mathcal{J}} \bar{P}(c, j)$$
(27)

³Here we attempt to clarify a couple points to the reader. Firstly, there may exist (due to channel mapping granularity restrictions) modes that propose infeasible solutions to the optimization subproblem, and secondly, not all modes in $\mathcal{K}_e(s)$ yield the most energy efficient AMC mode selection. We emphasize the purpose of this set is to determine a small subset of all possible AMC modes to perform the above optimization in order to reduce the search space.

TABLE II SIMULATION PARAMETERS

Parameter	Value	
Number of Antennas (M_T, M_R)	8	
Valid Spectral Efficiencies (M)	$\{0, 1.5, 3, 4.5, 6\}$	
Length of Packet (L_i bits)	200	
Arrival Rate ($\overline{\lambda_i}$ packets/frame)	2	
Buffer Size (B_i packets)	25	
Average Packet Delay (\mathcal{D}_i frames)	4	
Total Loss Rate (δ , % of Packets)	10%	
Target Channel Loss Rate $(P_{l,i})$	$\delta/2$	
Symbols per Frame per Channel (T_f/T_s)	200	
MAC Rates (C, packets/frame)	$\{0, 1, 2, 3\}$	
Number of independent scatters (L)	4	
Scatter relative power (P_l)	$\{0.4 \ 0.3 \ 0.2 \ 0.1\}$	
Number of channel partitions (\mathcal{J}_{ℓ})	5	
Reference SNR (γ_0)	10dB	

As in [1], the above framework can solve for all quantities offline and in advance, where the resulting resource allocation quantities can be stored in a look up table (LUT) at the base station. Full details of the LUT are available in [1].

IV. FORMULATION OF PROGRAMMING ELEMENTS

The channel, rate and power allocation described in the previous section can be formulated using the well-known branch and bound technique. The branch and bound algorithm can be used to solve a LP problem where one or more components of the solution vector are Integers. A general branch and bound problem is formulated to solve $f(\mathbf{x}) = \arg\min \mathbf{c}^T \mathbf{x}$ subject to $\mathbf{A}\mathbf{x} \leq \mathbf{b}$, $\mathbf{A}_{eq}\mathbf{x} = \mathbf{b}_{eq}$ and $\mathbf{x} \geq 0$ where \mathbf{A} and \mathbf{A}_{eq} are matrices, \mathbf{b} , \mathbf{b}_{eq} and \mathbf{c} are vectors and some or all entries in \mathbf{x} are constrained to Integers.

The vector **x** is a $LK \times 1$ vector with Integer elements $\bar{X}_{\ell,i}, \ell = 1, 2, \dots, L, i = 1, 2, \dots, K$ given as

$$\mathbf{x} = [\bar{X}_{1,1}(s), \ \dots, \ \bar{X}_{1,K}(s), \ \dots, \ \bar{X}_{L,K}(s)]^T$$
(28)

The objective function from (25) can be described as a coefficient vector \mathbf{c} with entries

$$\mathbf{c} = [\zeta_{1,1}(s), \dots, \zeta_{1,K}(s), \zeta_{2,1}(s), \dots, \dots, \zeta_{L,K}(s)] \quad (29)$$

where $s \in S$ and $\zeta_{\ell,i}(s)$ is

$$\zeta_{\ell,i}(s) = P(i,\ell,\mathcal{J}_{\ell}(s),k'_{\mathfrak{F}(\ell)}) \left[\frac{L_i}{k'_{\mathfrak{F}(\ell)}}\right]$$
(30)

A. Equality Constraints

The K equality constraints from (12) are given in the $K \times LK$ matrix \mathbf{A}_{eq} with entries

$$A_{eq:i,z} = \begin{cases} 1, z \in \mathcal{I}_i \\ 0, otherwise \end{cases}$$
(31)

where \mathcal{I}_i is the set containing location indices of $\overline{X}_{\ell,i}, \forall \ell$ in **x**. The coefficient vector \mathbf{b}_{eq} is subsequently given as

$$\mathbf{b}_{eq} = [c_1(s)L_1, \ c_2(s)L_2, \dots, \ c_K(s)L_K]^T \qquad (32)$$

where $c_i(s)$ is the number of packets taken from queue *i* when the system is in state *s*.



Fig. 2. Total average power vs. delay and arrival rate.

1) Inequality Constraints: The L equality constraints from (13) are defined in the $L \times MK$ matrix A with entries

$$A_{\ell,z} = \begin{cases} 1, z \in \mathcal{I'}_{\ell} \\ 0, otherwise \end{cases}$$
(33)

where \mathcal{I}'_{ℓ} is the set containing location indices of $\bar{X}_{\ell,i}, \forall i$ in **x**. The vector **b** is given as

$$\mathbf{b} = \frac{T_f}{T_s} [k'_{\mathfrak{F}(1)}, \ k'_{\mathfrak{F}(2)}, \dots, \ k'_{\mathfrak{F}(L)}]^T$$
(34)

V. RESULTS

Selected simulation results are presented using parameters as given in Table II demonstrating the total average power level selection as well as the effect of channel partitioning.

A. Average Power Usage

In Fig. 2 we show the average power performance as a function of the delay constraint and arrival rate in using our newly extended PHY with the MAC in [1]. As expected, the power performance is largely dominated by the average arrival rate. Further, and as expected, the average power is related to the delay in that an increase in the delay tolerance reduces the total average power (albeit at a lesser impact than the average arrival rate). This is a result of the system being able to exploit channels higher SNR states, for higher rate transmission. Further, we see that a region of arrival rate/delay constraints is infeasible as a result of the set of MAC service rates employed. This is also consistent with well-known queueing theory stability results.

B. Partitioning Performance

The number of channel partitions has a large impact on system performance. In Fig. 3 we show the impact on the number of partitions contrasted with the average power consumption. The computation time is measured with respect to the base case of 2 partitions per subchannel. On the one hand, we show that increasing the number of partitions increases the power efficiency of the system by allowing a greater degree of adaptability, however, the resulting complexity increases (resulting in increased computation time). Further, the memory



Fig. 3. Effect of channel partitioning.

requirement for the size of the lookup table greatly depend on the number of partitions. It is given as

$$SIZE_{LUT} = 64(2K+1)L\prod_{i=1}^{K} |\mathcal{C}_i| \prod_{\ell=1}^{L} |\mathcal{J}_\ell|$$
 bits (35)

where all relevant parameters are assumed to be stored as 64 bit doubles.

VI. CONCLUSION

In this paper, we extended our previous work in [1] to a packet based transmission scheme. This proposed framework presents a method of incorporating coded adaptive modulation schemes in the optimization framework. As a result, the work from [1] can be extended to more general multi-channel models and modulation schemes. In addition, we also study tradeoff of channel partitioning on average transmission power and computational complexity.

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