Multimedia Traffic Robustness and Performance Evaluation on a Cross-Layer Design for Tactical Wireless Networks

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***Abstract*—In this paper, we evaluate the importance of evaluating joint cross-layer strategy for a tactical wireless network with more adjusted application data traffic models. At first, we describe the system performance difference depending on the adopted traffic model. Besides that, considering our system queue model, several numerical results show the impact of physical, data-link, and application layer features over typical system metrics, such as average spectral efficiency and dropping probability.**

***Index Terms*—Cross-layer design, adaptive modulation, performance evaluation, wireless networks.**

I. Introduction

Several works in the literature have designed new mechanisms that allow a broader knowledge over traditional modular design scheme to study network layers relationships. Under such mechanisms, the classical independent layers paradigm is left aside for adoption of a *cross-layer optimization* (CLO) design. In a CLO design, parameters and functionalities from application, transport, network, data-link and physical layers are adjusted in an integrated fashion, enhancing overall system performance. Recently, in order to optimize system performance, research efforts have been specially focused on physical (e.g, adaptive modulation and coding techniques) and data-link layer (for instance, dropping probability over finite-length queues) enhancements. Thus, several parameters and models have been proposed to perform optimization under cross-layer frameworks for wireless systems like military tactical networks [1], [2], [3], [4], [5], [6], [7].

In general, such proposals focus on developing cross-layer designs that rely solely on the channel state, dealing independently with losses due to transmission errors at the physical layer and overflow effects at the data-link layer, without considering the impact of data traffic pattern on adaptive modulation threshold choices. For example, adaptive modulation thresholds optimization in [1], [2], [4], [5], [7] are evaluated to minimize a strictly physical-layer error rate over the system - thus, only physical-layer-driven thresholds are obtained. After this, system parameters, like dropping probability, packet loss rate or data-link transmission delay are indirectly evaluated, since they can only be determined after a suitable physical-layer-driven thresholds choice. Delay and overflow requirements are not taken into consideration.

Future tactical wireless networks are envisioned to support high data rates with a wide range of quality of service (QoS) requirements [8]. Thus, issues such as throughput, delay, packet error rate (PER), and packet overflow ought to be considered. Considering such features, we proposed in [9] a technique for physical-layer adaptive modulation thresholds optimization which takes into account wireless channel state and data-link layer queue behavior.

In the other hand, the authors in [10], [11] consider the buffer and traffic information over the adaptive modulation techniques set, but neither present important traffic model features, such as burstiness and batch arrival events, nor they evaluate the gain by adopting more elaborate application data traffic models, by comparing them with simpler descriptions. In order to enhance this new cross-layer design strategy with more accurate application data traffic models, we developed the Generalized Input Deterministic Service (GIDS) model in [12], which deals with generalized data traffic input under time-correlated service disciplines. In [13], we enhance this idea by introducing a queueing model based on embedded Markov-chain techniques that considers time-correlated arrivals with deterministic-time batch services on a finite-buffer queue, with capacity for B customers at a time, the MM $\sum_{k=1}^{K}$ CPP/D^{Y}/1/B queue - the

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Generalized Batch Input Deterministic Service (GBIDS) queue.

In this article, we evaluate the sensitivity of the joint cross-layer optimization technique in [9], now upgraded for the more accurate application data traffic models presented in [12], [13]. Differently from other works, our physical-layer adaptive modulation thresholds optimization takes into account not only wireless channel state and data-link layer queue behavior, but also application data traffic states - thus, we study the traffic model impact over system performance. Besides that, we also sketch channel parameters influence over the proposed framework.

The remainder of this work is organized as follows: the scenario of interest is described in Section II and an updated cross-layer optimization (CLO) design strategy is presented in Section II. Simulation results are presented and analyzed in Section IV, followed by concluding remarks in Section V.

II. Problem Statement

Among several military wireless networks, tactical data distribution systems (TDDS) [8] are assumed as a data service transmission upon an end-to-end wireless connection between an infantry or cavalry brigade and each subordinate batallion at combat, improving situational awareness and supporting command, control, and mobility issues. Thus, we consider an end-to-end wireless connection between a source (e.g., an infantry batallion) and a destination station (for instance, a brigade command headquarters), through a single-transmit single-receive transmission setup using a time-slotted medium access technique, as illustrated in the agregated channel-queue model presented in Figure 1, which describes the channel-queue model for a given pair i.

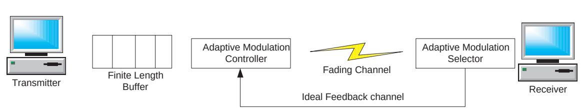

Figure 1. TDDS channel-queue model.

The finite-buffer queue feeds an adaptive modulation controller at the transmitter. The receiver feeds back the channel state information (CSI) to the transmitter by an ideal reverse channel, admitted as error- and delay-free. The transmitter uses CSI, the queue state, and the application data traffic rate to choose the modulation scheme. It is worth noting that each packet may be transmitted successfully, dropped, due to buffer overflow, or lost at the corresponding base station, in case of transmission errors.

1) Channel-Queue Model: In wireless mobile networks, overall system performance degrades markedly due to time-dispersive effects introduced by the wireless propagation environment. We adopt a time-varying wireless channel, characterized by flat fading effect, in which we consider that the channel remains invariant during each frame transmission. Such frame transmission temporal variation is modelled by a wide-sense stationary process with Jakes spectrum whose maximum Doppler frequency shift is f_D. Instantaneous signal-to-noise ratio γ is modelled by a probability density function $p(\gamma, \overline{\gamma})$, where $\bar{\gamma}$ represents average signal-to-noise ratio.

In order to enhance the spectral efficiency while adhering to a target error performance over wireless channels, adaptive modulation is used to match transmission parameters to time-varying channel conditions. We assume that N transmission modes are available for the transmitter, with each mode representing a specific modulation scheme, which is chosen based on an ideal channel-state information at the receiving station and on data-link buffer occupancy at the transmitting station. This channel-state information is sent to the transmitter by an ideal feedback channel, admitted as error- and delay-free. Transmission mode n is adopted by transmitter-receiver pair when instantaneous signal-to-noise ratio (SNR) γ lies between γ_n and γ_{n+1}.

When mode n ($n \in \{1, ..., N\}$) is used by the transmitter, the outgoing packet is encoded in a block with N_b/R_n symbols, where R_n represents transmission mode n spectral efficiency. Afterwards, each block fills one single frame data slot. After aggregating N_d blocks, the frame is transmitted over the wireless adaptive channel with physical-layer bit error rate given by $BER(\gamma)$, according to instantaneous signal-to-noise ratio γ.

Each block is filled into a frame time slot, where each time slot holds N_b symbols; thus, the maximum number of transmitted packets per time slot (R_n) depends on the adopted modulation scheme. These aggregate packets are transmitted over the wireless adaptive channel subject to physical-layer packet errors, data-link dropping events, and delay effects due to finite length buffer.

Each time frame has a fixed time duration of T_{ts} seconds, being divided into N_d time slots for data and N_c time slots for control information, containing a fixed amount of N_s symbols. Thus, a single frame *i* refers to time period $[(i-1)\, T_{ts}, iT_{ts})$ seconds. The transmitter station has a finite-length buffer, with capacity of B packets. Each packet has a fixed length of N_b bits, divided into header, data and checksum bits.

So, if a packet arrives when the buffer is full, it is discarded and lost. We assume that the channel-queue behavior, comprising features like f_D, γ, and queue occupancy, can be modelled as a Finite State Markov Chain described by the matrix X, with $N+1$ states (the first state, namely state 0, indicates no-transmission option) under slow fading conditions, so that transitions happen only between adjacent states.

2) Application Data Traffic Model: A model description for a application data traffic for a single link is depicted in Fig. 2. Packet arrivals at the queue, denoting different multimedia traffic sources, are represented by the superposition of K independent discrete-time Markov-Modulated Poisson processes (d-MMPP) A_1,A_2,...,A_K. Each d-MMPP process has m states or *modulation phases* [12]. It is worthwhile noting that a single d-MMPP A_i can be fully described by parameter matrices T_i and Λ_i, which represent the transition probability matrix of the modulating Markov chain and the matrix of Poisson arrival rates for process *i*, respectively.

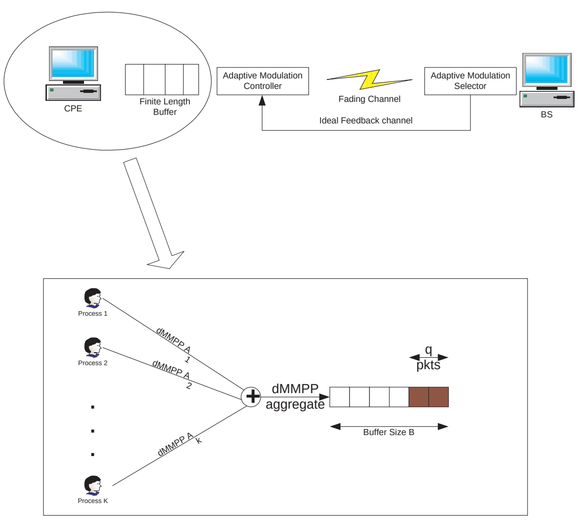

Figure 2. Model description for a generic application data traffic model.

The sequence of arriving-batch sizes for each d-MMPP process l is given by $\left\{X_i^l\right\}_{i=1}^{\infty}$, which is composed of independent and identically distributed (IID) random variables and X_i^l has the probability mass function (PMF) $P(X_i^l = j) = p_j, j = 1, 2, ...,$ where j stands for the batch size.

The overall customer arrivals aggregate is given by the superposition parameter matrices T and Λ, where $T = T_1 \otimes T_2 \otimes ... \otimes T_K$ and $\Lambda = \Lambda_1 \oplus \Lambda_2 \oplus ... \oplus \Lambda_K$, with $\oplus$ and $\otimes$ denoting the Kronecker sum and the Kronecker product, respectively.

3) System Analysis: We state that the overall system queue discipline, comprising both time-correlated services due to adaptive modulation features and multimedia data traffic arrivals in batches, can be described by a MM $\sum_{k=1}^{K}$ CPP/D^Y/1/B queue model, from now on denoted as Generalized Batch Input Deterministic Service (GBIDS) model, which describes transition probabilities for every combination (i.e., modulating phase) of batch arrival and service processes.

The associated Markov chain for GBIDS is given by $\mathbf{D}$, where $\mathbf{D} = \mathbf{T} \otimes \mathbf{X}$, representing a d-MMPP of order $F = K.m.n$, where F represents total number of modulating phases. For $n \geq 1$, Q_n^- describe the number of customers in the queue just before the *n*th service batch departure, Y_n denote the *n*th service batch size and A_n represent the number of customers that arrive between *n*th and *n+1*th service times, including possible blocked ones, defining a *left-service*-epoch embedded Markov chain $\mathbf{Q}$. As stated in [13], we assume that the stationary queue length distribution at that epoch is ergodic.

So, $\mathbf{Q}$ is a process recursively described by:

$$Q_{n+1}^- = \begin{cases} \min(Q_n^- - Y_n + A_n, B) & \text{if} \quad Q_n^+ \geq Y_n \\ \min(A_n, B) & \text{if} \quad Q_n^+ < Y_n \end{cases} \tag{1}$$

We define $c_{j,f}$ as the probability of arriving j customers during service departures when the overall system is on phase f, considering the probability of batch arrivals. Let also $P_{k,f}^-$ be defined as the probability of having k customers in the system immediately before a service departure on phase f. The stationary queue-length distribution $P_{k,f}^-, k = 0, 1, ..., B$ and $f = 1, ..., F$ is determined by

$$P_{k,f}^- = \sum_{b=0}^{B} \sum_{g=1}^{F} P_{b,g}^- . c_{q,g} . D_{g,f} \text{ , for } 0 \leq k < B \tag{2}$$

$$P_{k,f}^- = \sum_{b=0}^{B} \sum_{g=1}^{F} P_{b,g}^- . (\sum_{s=q}^{\infty} c_{s,g}) . D_{g,f} \text{ , for } k = B \tag{3}$$

where $q = k - b + \max(b - g, 0)$ and $D_{g,f}$ represents transition probability from state g to state f. The normalization condition is

$$\sum_{b=0}^{B} \sum_{g=1}^{F} P_{b,g}^- = 1 \tag{4}$$

Based on $P_{k,f}^-$, we can evaluate the stationary queue-length distribution at an arbitrary epoch, given by $P_{k,f}$, where, due to Markov Renewal theory [12]:

$$P_{k,f} = \sum_{n=0}^{k} \sum_{g=1}^{F} P_{n,f}^- D_{g,f} \int_0^x c_{k-n,f}(x) \frac{1}{T_{ts}} dx \tag{5}$$

where $c_{k-n,f}(x)$ stands for the probability of arriving $k-n$ customers at phase f during a time interval x, where $0 \leq x \leq T_{ts}$.

III. Design Proposal

Our goal is to identify physical-layer adaptation thresholds that optimize global parameters, like system throughput and packet loss rate, in a direct fashion, according to simultaneous information from all layers. So, using the technique proposed in our previous work [13], we evaluate the following quality of service metrics in this work:

- Data-link layer spectral efficiency ($S_{e,\bar{\gamma}}$): average number of bits transmitted per symbol through a wireless channel with average SNR given by $\bar{\gamma}$;
- Average packet error rate (P_o): losses due to physical layer transmission errors;
- Dropping probability (P_d): losses due to overflow events at data-link transmission queue;
- Packet loss rate (ξ): physical- and data-link-layer losses aggregate.

In spite of their advantages, the methods presented in [1], [2], [4], [5], [7] have some drawbacks. First of all, it is impossible to evaluate system throughput and overall packet loss rate directly, since these tasks can only be performed after determining an optimal packet error rate at physical layer. Besides that, such procedure does not ensure that optimal setting will be determined; this statement holds since the choice of adaptive modulation thresholds impact on both physical and data link layer. The main limitations of this policy is that it does not guarantee any application- or data-link-dependent requirements. Finally, they do not consider the impact of more realistic data traffic patterns on adaptive modulation thresholds choice.

Thus, in this article, we evaluate a more accurate queue system model, namely the GBIDS framework [13], under the CLO strategy proposed in [9]. Our objective is to identify the cross-layer design technique robustness to the adopted data traffic models. So, the conducted physical-layer adaptive modulation thresholds evaluation takes into account traffic and buffer states in addition to channel state to choose the action to be applied in a particular system state. This policy guarantees a joint cross-layered requirements set. In this adaptation scheme, each system state has a unique optimal action and corresponding transmission rate. So, we keep on targetting system settings optimization solving the problem in a joint fashion, but now with more realistic application data traffic assumptions.

We state that packet loss events depend not only on physical layer parameters $(m, f_D, \bar{\gamma})$ but also on upper layer settings, like data link queue length (K), packet arrival traffic rates and states (matrices T and Λ), and transmission frame duration (T_{ts}). Both types of parameters impact on the choice of the adaptive modulation thresholds set Γ and, as a consequence, on the probability of choosing a particular mode n for transmission, depending on current queue occupancy state ($Pr(n)$), where:

$$\Gamma = [\gamma_1, \gamma_2, ..., \gamma_N]^T \tag{6}$$

$$Pr(n) = \int_{\gamma_n}^{\gamma_{n+1}} p_\gamma(\gamma) d\gamma \tag{7}$$

Given π (stationary distribution of traffic-channel-queue model), which is based on the stationary queue-length distribution at an arbitrary epoch $P_{k,f}$, representing k customers at an arrival-service phase f, we define the following metrics for each transmission mode n:

- Utilization (U_n): transmission probability at mode n. Such transmission events occur when there are at least n packets in queue. In mathematical notation, $U_n = \sum_{j=n}^{j=K} \pi(Q = j, mode = n)$, where Q represents the number of packets in queue and $\pi(Q = j, mode = n)$ describes the probability of having j packets in queue when the transmission mode is n.
- Dropping (D_n): packet dropping probability upon queuing at mode n. This occurs when the number of arriving packets is higher than available space in queue. In mathematical notation, $D_n = \sum_{j=0}^{j=K} P(A_t > K - j)\pi(Q = j, mode = n)$.

At transmission mode n, data-link layer spectral efficiency ($S_{e,n}$), average packet error rate ($P_{o,n}$) and packet loss rate (ξ_n) are represented by:

$$S_{e,n}(\Gamma) = n \times U_n \tag{8}$$

$$P_{o,n}(\bar{\gamma}) = \sum_{j=1}^{N_b} \binom{N_b}{j} BER(\bar{\gamma})^j (1 - BER(\bar{\gamma}))^{(N_b - j)} \tag{9}$$

$$\xi_n = D_n + (1 - D_n) P_{o,n} \tag{10}$$

Thus, overall system metrics, like packet loss rate ξ and data-link layer spectral efficiency $S_{e,\bar{\gamma}}(\Gamma)$ are given by:

$$\xi = P_d + (1 - P_d) P_o \tag{11}$$

$$P_o = \frac{\sum_{n=1}^{N} n \times Pr(n) \times U_n \times P_{o,n}}{\sum_{n=1}^{N} n \times Pr(n) \times U_n} \tag{12}$$

$$P_d = \sum_{n=1}^{N} D_n Pr(n) \quad (13)$$

$$S_{e,\bar{\gamma}}(\Gamma) = \sum_{n=1}^{N} S_{e,n}(\Gamma) \times \pi_n \quad (14)$$

Our proposal aims to determine a set Γ^*, with N adaptive modulation thresholds, which maximizes $S_{e,\bar{\gamma}}$ with minimum packet loss rate provided by ξ_{min}. This formulation is described as follows:

$$S_{e,\bar{\gamma}}(\Gamma^*) = \max S_{e,\bar{\gamma}}(\Gamma) \qquad s.t.\ \xi = \xi_{min} \quad (15)$$

where $\Gamma \in \mathbb{R}^N$.

As described previously in [9], our proposal encompasses two steps:

- Minimum packet loss rate determination(ξ_{min}), based on a suitable adaptive moduation thresholds identification $\{\gamma_n\}_{n=1}^{N}$.
- Channel-queue model evaluation, based on a discrete-time Markov chain (DTMC), to identify quality of service metrics of interest and maximum $S_{e,\bar{\gamma}}$, given by $S_{e,\bar{\gamma}}(\Gamma^*)$.

IV. Numerical results

Traditional cross-layer design proposals [2], [4], [1], [7], [5] evaluate several system parameters, such as dropping probability, average queue delay, packet loss rate, and average system throughput by adopting a Poisson arrival process, without taking more realistic traffic models into account. In our first case study, we compare Poisson- and GIDS-driven queue occupancy distribution.

We consider a transmitter with six available transmission modes, namely non-transmission mode, BPSK, 4-QAM, 8-QAM, 16-QAM, and 32-QAM, where the non-transmission mode is adopted in case of severe fading conditions. As described in the previous study case, these transmission modes describe packet service process phases. We adopt Γ as an adaptive modulation thresholds vector, where $\Gamma = [7,4062; 9,2711; 15,2856; 16,6486; 20,8606]$ dB in order to determine the adopted transmission mode in a time slot basis, taken as $T_{ts} = 2$ ms. The vector Γ was chosen since it establishes a physical layer packet error rate equal to 10^{-2} for an average SNR of 20 dB in [1], and it defines the adopted service process transition probability matrix X. Thus, the batch service process is represented by a 6-phase model, which is suitable to represent a wireless channel under Rayleigh fading effects and fixed batch service disciplines of $n = \{0, 1, 2, 3, 4, 5\}$ served packets at each time slot, depending on fading channel conditions.

We consider two traffic models, according to Poisson and IPP (*Interrupted Poisson Process*) processes, both of them holding an average traffic rate of 2 packets per time-slot. We adopt $T = \begin{pmatrix} 0.8 & 0.2 \\ 0.12 & 0.88 \end{pmatrix}$ and $L = \begin{pmatrix} 0 & 0 \\ 0 & 1600 \end{pmatrix}$ as the IPP-traffic parameters, average signal-to-noise ratio $\bar{\gamma} = 20$ dB, maximum Doppler frequency shift $f_D = 10$ Hz, and queue length $B = 100$ packets.

Table I presents packet loss rate (ξ), dropping probability (P_d) and average spectral efficiency ($\bar{S}$) values for three different scenarios, namely the one presented in [1] (LZG) as an example of the traditional cross-layer design approaches, and our proposal (MSG) with Poisson and IPP traffic models.

Table I
Case Study - Comparison between traditional and GIDS-driven cross-layer design approaches.

	LZG	**MSG + Poisson traffic**	**MSG + IPP traffic**
PER	0.01	0.01	0.01
P_d	0.0097	0.0096	0.0130
ξ	0.0196	0.0195	0.0228
$\bar{S}$	2.4277	1.9711	1.9477

We can observe that LZG model can be taken as a particular MSG model case regarding a Poisson traffic arrival process. Physical-layer packet error rate values are the same as expected, given that the steady-state probabilities for transmission mode adoption strictly rely on Γ. Average spectral efficiency differences are due to the fact that the MSG model only allows the transmission of a number of packets equal to block size. On the other hand, the LZG method grants packet transfers even below the block data filling level at a given time-slot.

It is also worth noting that LZG model does not properly fit in IPP-traffic cross-layer design case, since it produces noticeable differences for the remaining performance metrics, such as dropping probability P_d. Thus, we perform an additional study case, in order to determine a suitable Γ vector to achieve the same ξ value (ξ =0.0196) for IPP as obtained for previous case study Poisson traffic model, given an identical average arrival rate. We adopt the same T, L, $\bar{\gamma}$, f_D, and B values as in the first study case. Table II describes the achieved values:

Comparing the results from Tables I and II, we observe that the thresholds vector gets more conservative for IPP-traffic than in Poisson traffic case - i.e., each modulation scheme is used under higher SNR values. As a con-

Table II
CASE STUDY - OPTIMIZED SYSTEM PARAMETERS FOR IPP TRAFFIC.

Metric	Value
PER	0.0059
P_d	0.0137
Γ	[8.6350; 10.9479; 17.1120; 18.6771; 23.2709]
S	1.9469

sequence, the IPP traffic experiences a lower physical-layer error rate ($0.0059 < 0.01$); on the other hand, there is a higher packet dropping probability ($0.0137 > 0.0097$), due to the higher packet arrival rate observed during transmission periods ($P_{on} = 0.625$). So, we state that it is not sufficient to take Poisson-driven results as a standard for other traffic models with the same packet arrival rate, due to the noticeable performance differences - different adaptive modulation thresholds and system performance. Moreover, a physical-layer-only adaptive modulation technique is insufficient to guarantee desirable quality of service levels. In fact, it is necessary to take higher layers' parameters into account to produce system performance optimization.

In the following case study, we compare the system performance values for Poisson and IPP traffic models with equal average packet arrival rates. If they were similar, it could be reasonable just to take Poisson-case vector into account to evaluate optimal performance for every traffic model, due to its simplicity. Considering average packet arrival rate $\lambda T_{ts} = 2$ packets per time slot, maximum Doppler frequency shift $f_D = 10$ Hz, and queue length $B = 20$ packets, both Poisson and IPP traffic models were evaluated. The adopted IPP matrices were $T = \begin{pmatrix} 0.8 & 0.2 \\ 0.4 & 0.6 \end{pmatrix}$ and $L = \begin{pmatrix} 0 & 0 \\ 0 & 3000 \end{pmatrix}$. As a final test, the threshold vector adjusted for a Poisson traffic was used for the IPP data traffic source, to evaluate the performance impact.

Figure 3 help us to observe that the average spectral efficiency is severely degraded for the IPP traffic model, due to the upsurge of packet dropping effects during IPP transmission periods. In 4, we see that the packet loss rate is specially subject to the average SNR values. The performance of the IPP model is better on higher average SNR values, since more efficient modulation schemes are adopted, which is more interesting for traffic models with higher burstiness, while the opposite holds for lower average SNR values. We can also observe that the IPP model performance with Poisson-adjusted thresholds is significantly worse - higher packet loss rate and lower average spectral efficiency - than the one with a properly IPP-adjusted vector.

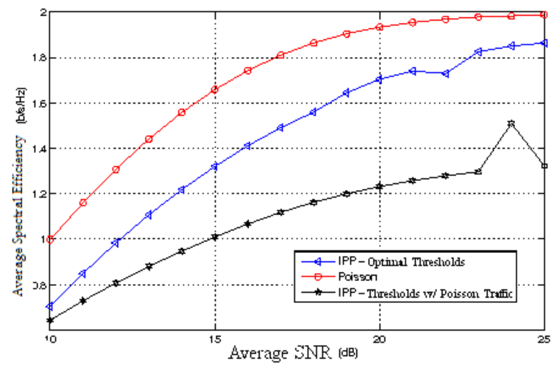

Figure 3. System throughput - Traffic Models Comparison.

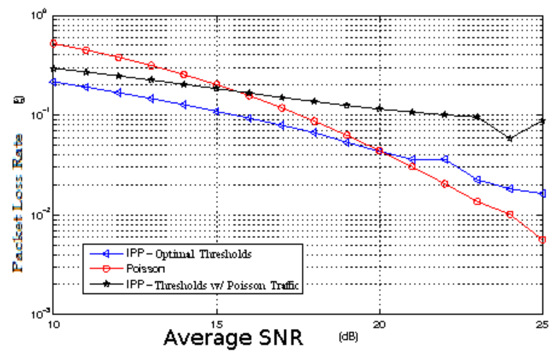

Figure 4. Packet Loss Rate - Traffic Models Comparison.

Thus, we state that the system performance is highly influenced by the adopted traffic model. Besides that, it is not reasonable to simply adopt Poisson-driven adaptive modulation threshold vector for IPP traffic scenarios, since we observe an average spectral efficiency decrease and a packet loss rate increase in the whole average signal-to-noise interval range.

After identyfing the need for considering more accurate traffic models, we submit a IPP traffic with matrices $T = \begin{pmatrix} 0.8 & 0.2 \\ 0.3 & 0.7 \end{pmatrix}$ and $L = \begin{pmatrix} 0 & 0 \\ 0 & 3000 \end{pmatrix}$ over a system with transmitter queue length given by $B = 20$ and 40 packets, minimum achieved packet loss rate ξ_{min} and average spectral efficiency ($\bar{S}$) are evaluated in order to analyze queue length influence. The results obtained are shown in Fig. 5 and 6.

Figures 5 and 6 show that the increase in queue length offers a small $\bar{S}$ increase for lower average SNR values. This result for higher SNR values is due to the adoption of transmission modes with higher spectral efficiency for both queue length values, conjugated with the small packet dropping probabilities verified on those scenarios. We confirm that increasing queue length B decreases

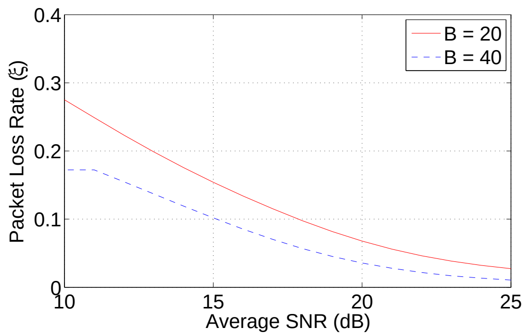

Figure 5. Queue length influence on ξ over SNR range.

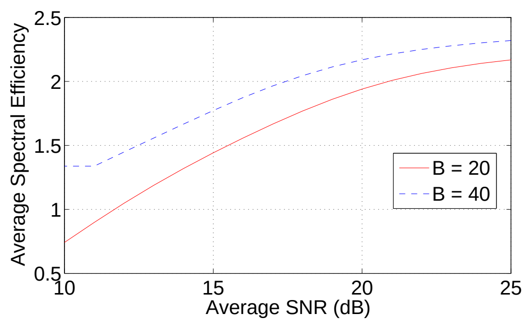

Figure 6. Queue length influence on $\bar{S}$ over SNR range.

packet loss rate ξ, as stated by the authors in [9].

After that, we also evaluate arrival data rate influence on minimum achieved packet loss rate ξ_{min} and $\bar{S}$, just by comparing two traffic data sources with different arrival data rates, described by matrices $L_1 = \begin{pmatrix} 0 & 0 \\ 0 & 3000 \end{pmatrix}$ and $L2 = \begin{pmatrix} 0 & 0 \\ 0 & 6000 \end{pmatrix}$, respectively. Numerical results shown in Fig. 7 and 8 were obtained for queue length $B = 20$ packets. As mentioned by the authors in previous works, increasing arrival data rate leads to higher ξ values; however, it improves $\bar{S}$, since there are more available packets to be transmitted per data-unit, specially for higher average SNR values, due to the adoption of higher spectral efficiency transmission modes.

Finally, we consider traffic burstiness influence on minimum achieved packet loss rate ξ_{min} and $\bar{S}$, just by comparing two traffic data sources with $P_{on} = 0.4$ and $P_{on} = 0.6$, respectively. Numerical results shown in Fig. 9 and 10 were obtained for average packet arrival rate $\lambda T_{ts} = 2.4$ packets per time slot, maximum Doppler frequency shift $f_D = 10$ Hz, and queue length $B = 20$ packets.

For this study case, we can observe that the model

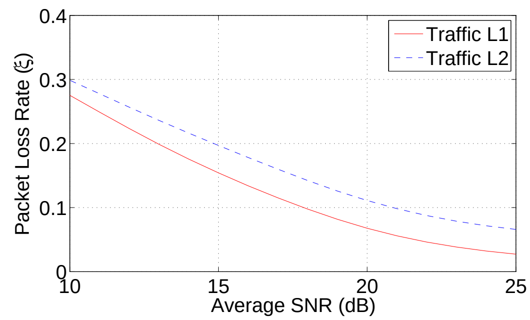

Figure 7. Arrival Data Rate influence on ξ over SNR range.

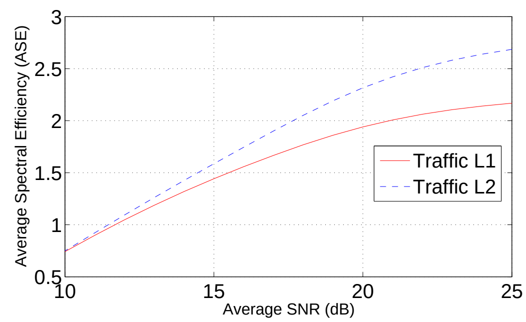

Figure 8. Arrival Data Rate influence on $\bar{S}$ over SNR range.

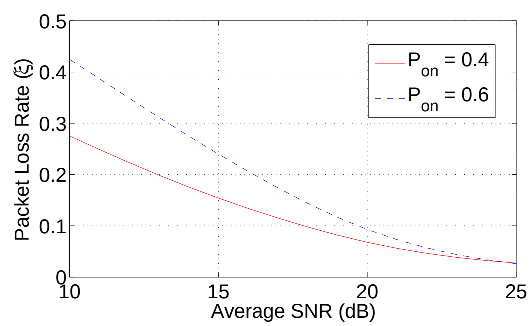

Figure 9. Arrival Data Rate influence on ξ over SNR range.

with higher transmission period (P_{on}) presents a higher $\bar{S}$. This is reasonable since, for a given time-slot period, there are more available packets to be transmitted for $P_{on} = 0.6$. By the other way, such transmission period increase also leads to higher ξ values, specially for lower average SNR values, due to higher packet dropping probability. The amount of dropping events decreases for $P_{on} = 0.4$ because there are less packets arriving during the time slots in which few or even no packets are served.

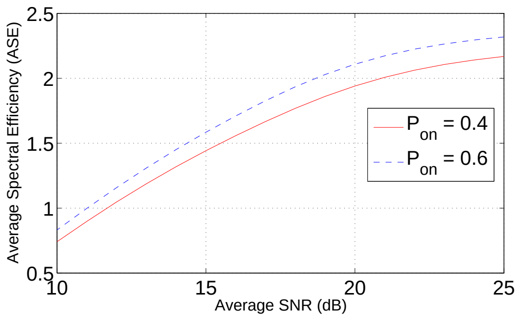

Figure 10. Arrival Data Rate influence on $\bar{S}$ over SNR range.

V. Conclusion

In this paper, we developed a cross-layer design procedure to improve system performance for transmissions over adaptive wireless networks. Taking previous works as starting points, we presented a direct design approach which maximizes average spectral efficiency subject to an overall target packet loss rate, which combines errors from physical and data link layers considering more accurate data traffic models. We performed changes on data traffic patterns, wireless channel models and QoS performance metrics [12], in order to check the amplitude of such advantages taken from joint CLO design frameworks, analyzing system effects over typical wireless tactical systems.

We observed that traditional cross-layer design approaches do not properly fit for more elaborated traffic models, since they produce noticeable differences in important system performance metrics. We also stated that the system performance is highly influenced by the adopted traffic model, and it is not reasonable to simply adopt Poisson-driven adaptive modulation threshold vector for IPP traffic scenarios. Finally, we studied the influence of physical, data-link and application layer features over noticeable performance metrics, indicating their close dependence on application layer features such as data rate and burstiness.

There are several possible ways to extend the results presented in this paper. One direction is to improve system performance by an association between application data traffic burstiness and adaptive modulation thresholds optimization, by the evaluation of a suitable threshold vector for each data arrival rate. Another direction is to evaluate the impact of feedback channel imperfections over the system performance. Finally, we can consider the case multiple transmitters want to maximize their revenues in the same environment. In this case, it is important to consider the interactions among different users, under a multitude of channel, interference, buffer, and application combinations.

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