Impact of Channel Modeling on the Performance of Wireless Scheduling Schemes

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Abstract— **Wireless packet scheduling schemes provide the means to achieve service differentiation for wireless users with diverse quality-of-service (QoS) demands. These schemes are often designed to account for the dynamics of the wireless channel, so that a user that is *likely* to experience deep fade defers his transmission until the channel conditions improve. The vacant transmission slot is then given to another user that is expected to experience a "clean" channel. Channel conditions are location dependent and are made available to the transmitter (the scheduler) after some time delay. Therefore, at the time of packet scheduling, the scheduler has to *predict* the current channel state at a given receiver, often based on an N-state Markov model. The goal of this paper is to assess the impact of channel predictions on the delay and throughput performance obtained under two popular wireless scheduling schemes. For both schemes and under reasonble channel assumptions, we show that better performance can be achieved by increasing N.**

I. Introduction

Packet-level service differentiation is typically achieved by means of scheduling. For wireless cellular networks, scheduling is performed by the base station for both downlink and uplink flows. The design of a"fair" scheduling algorithm that simultaneously provides performance guarantees is a challenging task because of the need to account for the time-varying and receiver-dependent characteristics of the wireless medium and to reduce packet retransmissions to conserve battery energy.

Several wireless scheduling algorithms were previously proposed to achieve fairness and provide QoS guarantees; examples are found in [1, 5, 6, 7, 4]. Many of these algorithms use a *service compensation* mechanism to achieve fairness while providing short- and/or long-term guarantees on throughput and delay. With such a mechanism, if a flow that is about to start a packet transmission perceives a "bad" channel (e.g., no ACK arrives from the receiver for the previous packet), then the transmission slot of this flow is given to another flow that perceives a "good" channel. At a later time, the flow that gained the extra slot relinquishes some of its service rights to other flows that previously deferred their transmissions.

An essential part of the service compensation mechanism is a channel predictor. Previously proposed scheduling algorithms rely on the so-called Gilbert-Elliot (GE) model to predict the state of the channel. The GE model is a two-state Markov model, where in one state the channel is extremely "bad" (bit error rate ≈ 0.5) and in the other state the channel is very "good" (BER ≈ 0). In practice, the channel state is determined by the signal-to-noise ratio (SNR) at the receiver. This SNR takes a continuous range of values. Discretizing the SNR into two regions that correspond to two states is a rather crude approximation. In [8] the authors used information theoretic arguments to show that the GE model minimizes the channel capacity. By employing a specific SNR partitioning approach, the authors in [2] showed that the *wireless effective bandwidth* increases dramatically as the number of states of the employed Markov model is increased. In other words, the 2-state GE model leads to a highly conservative allocation strategy. We show in this paper how the performance of wireless scheduling algorithms is affected by the employed channel and prediction models.

Without loss of generality, we consider two popular wireless scheduling schemes: Wireless Fair Service (WFS) [5] and Channel Condition Independent Packet Fair Queueing (CIF-Q) [7]. Both schemes are known to be fair and to provide delay and throughput guarantees. Our results are equally applicable to other scheduling schemes that employ channel prediction. To investigate the impact of the inaccuracy in channel predictions, we make a

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distinction between the *prediction model* and the *channel model*. The former refers to the model used by the scheduler to predict the channel state at a given receiver, while the latter refers to the stochastic process that drives the dynamics of the wireless channel. We investigate the effect of different prediction models under a given channel model, and vice versa.

The rest of the paper is organized as follows. In Section 2, we describe the channel and prediction models used in our study. In the same section, we describe the approach used to partition the SNR range and determine the parameters of the corresponding Markovian channel model. Our simulation-based results are provided in Section 3. Section 4 concludes the paper.

II. Channel Characterization

A. Channel and Prediction Models

For the channel models, we use Jake's simulation model as well as M-state Markov models ($M \geq 2$). Jake's model provides accurate characterization of the dynamics of a downlink channel with Rayleigh fading. However, it is specified by a large number of parameters. For Markov-based channel models, we consider two types. In the first type, the model parameters are obtained by partitioning the continuous SNR range into M states using the approach in [9] with some modifications (details are given in Section 2.2). The second type is the popular 2-state GE model but with parameter values that are obtained from Jake's simulator [3] (which gives the average packet error rate of the channel). When Jake's model is used to drive the channel dynamics, we allow the value of N in the predictor model to be arbitrarily large, whereas we restrict N to be less than or equal to M when using a Markov-based channel model.

The prediction models that we use are N-state Markov models, with $N \geq 2$. The case $N = 2$ is of particular interest, as it has often been employed in evaluating wireless scheduling schemes. Two types of 2-state Markov models are considered: a *binary-feedback* model and a *SNR-based* model. In the binary-feedback model, the receiver relies on the outcome of the decoding process to determine whether a packet is successfully received or not. This binary information is then fed back to the transmitter, which uses it to predict the future channel state. The binary-feedback model is employed with the GE channel model. In the 2-state SNR-based model, the received SNR values are themselves made available to the transmitter, which uses them to predict the future channel state. This model provides more accurate predictions than the binary-feedback model (when employed under an M-state Markov channel model). For $N > 2$, the prediction model is always SNR-based. Note that the nature of the prediction model has important ramifications on the adaptiveness of the employed forward error correction (FEC) scheme. For a 2-state model, transmission is allowed to proceed only if the channel state at the receiver is forecasted to be "good," in which case FEC is applied with a fixed code rate, i.e., the code is not adaptive. In contrast, for a higher-order model, the FEC capability can be changed adaptively depending on the predicted channel state (in this case, the transmission is allowed to proceed under all channel states except the worst one).

B. Channel State Partitioning

Markov-based channel modeling requires partitioning the continuous SNR range into a finite set of states. Several methods for SNR partitioning were proposed in the literature (e.g., [2, 8, 9]). Any of these methods can, in principle, be used in our work. Without loss of generality, we consider the partitioning scheme in [9] as the basis for our channel modeling. This scheme results in all states having the same mean sojourn time except for the last state (whose range extends to infinity). Let c_k be the mean sojourn time in state k ($k = 1, \ldots, M$). Then, c_k can be expressed in terms of the Doppler frequency (f_m), the packet transmission period (T_p), and the mean received SNR (ρ):

$$c_k = \frac{\exp\{-\frac{\Gamma_k}{\rho}\} - \exp\{-\frac{\Gamma_{k+1}}{\rho}\}}{\sqrt{\frac{2\pi\Gamma_k}{\rho}}\exp\{-\frac{\Gamma_k}{\rho}\} + \sqrt{\frac{2\pi\Gamma_{k+1}}{\rho}}\exp\{-\frac{\Gamma_{k+1}}{\rho}\}} \frac{1}{f_m\, T_p}, \quad k = 1, 2, ..., M \tag{1}$$

where $[\Gamma_k, \Gamma_{k+1})$ is the SNR range that corresponds to state k ($\Gamma_1 \stackrel{\text{def}}{=} 0$ and $\Gamma_{M+1} \stackrel{\text{def}}{=} \infty$). Under the constraint $c_k = c$, $k = 1, 2, \ldots, M-1$, and for a given c, the values of Γ_k, $k = 2, \ldots, M$, can be recursively obtained from (1). In [9] the authors suggest taking $c \approx 3$.

Once the SNR range has been partitioned, the transition probabilities for the underlying Markov chain can be obtained, as follows [9]:

$$\begin{aligned} P_{k,k+1} &\approx \frac{LCR(\Gamma_{k+1})T_p}{\pi_k}, \quad k = 1, 2, ..., M-1 \\ P_{k,k-1} &\approx \frac{LCR(\Gamma_k)T_p}{\pi_k}, \quad k = 2, ..., M \end{aligned} \tag{2}$$

where $LCR(x)$ is the level crossing rate at SNR level x, and is given by [8]:

$$LCR(x) = \sqrt{\frac{2\pi x}{\rho}} f_m \exp\left(-\frac{x}{\rho}\right) \tag{3}$$

and π_k is the steady state probability of being in state k:

$$\pi_k = \exp\left(-\frac{\Gamma_k}{\rho}\right) - \exp\left(-\frac{\Gamma_{k+1}}{\rho}\right). \tag{4}$$

In addition to partitioning the SNR range, the specification of the Markov model requires determining the average error rate (e_k) in each state k. For BPSK modulation, e_k is given by [8]:

$$e_k = \frac{\int_{\Gamma_k}^{\Gamma_{k+1}} \frac{1}{\rho} \exp\{-\frac{\alpha}{\rho}\}(1-F(\sqrt{2\alpha}))d\alpha}{\int_{\Gamma_k}^{\Gamma_{k+1}} \frac{1}{\rho} \exp\{-\frac{\alpha}{\rho}\}d\alpha}, \quad k = 1, \ldots, M. \tag{5}$$

where F is the standard normal distribution function. In [8] a simpler expression for e_k was obtained:

$$e_k = \frac{\gamma_k - \gamma_{k+1}}{\pi_k} \tag{6}$$

where

$$\gamma_k = \exp\left(-\frac{\Gamma_k}{\rho}\right)(1 - F(\sqrt{2\Gamma_k})) + \sqrt{\frac{\rho}{\rho+1}} F\left(\sqrt{\frac{2\Gamma_k(\rho+1)}{\rho}}\right). \tag{7}$$

In the above partitioning procedure, the value of M is not specified as an input, but is generated as an outcome of this procedure. So it is possible to end up with an excessively large M. To control the value of M, we extend the partitioning procedure in [9] as follows. We start with a crude 2-state partitioning of the channel, where the only unknown is Γ_2. We select Γ_2 to be the maximum possible SNR value that will result in an average *packet error rate* (PER) during state 1 (the bad state) that is greater than $\epsilon = 10^{-5}$ under the maximum allowed FEC code rate (which we set to $1/2$). Then, we generate a set of states $\mathcal{L}$ using the partitioning scheme in [9] with the value of c chosen so that the previously obtained Γ_2 is a boundary to one of the states in $\mathcal{L}$ (but not necessarily the first state). The size of the resulting $\mathcal{L}$ is 16 and $c \approx 3.1$. Then, starting from $\mathcal{L}$ we merge neighboring states to obtain the desired value of M. In doing so, we try to ensure that the resulting (reduced) set of states, denoted by $\mathcal{L}^*$, have the same mean sojourn time. We classify the states in $\mathcal{L}^*$ into "good" and "bad" states according to the mean PER during each state under 1/2 code rate; if this mean is greater than ϵ, the corresponding state is "bad"; otherwise, it is "good." Packet transmission is deferred in the "bad" states, and is allowed to proceed in the "good" states using a state-dependent FEC code rate.

III. Simulation Results

In the following simulations, we demonstrate the effect of employing various prediction and channel models at medium mobility (i.e., $f_m = 50$ Hz). We consider three mobile users and a base station. The throughput (normalized with respect to the traffic load) and the average packet delay are obtained for various utilization levels (U), defined as the ratio of the information rate (before FEC coding) and the channel bit rate. Throughout the simulations, we keep the size of the packet payload constant. The total size of a packet varies according to the number of FEC bits.

Figures 1 and 2 show the effect of employing different prediction models on the throughput and delay performance for the WFS scheduling algorithm, using Jake's simulator as the channel model. In the figures, we also provide the performance measures under the GE channel model. As shown in the figure, increasing N from 2 to 4 results in a good improvement in the throughput and, simultaneously, a reduction in the average packet delay. The difference in throughput between the cases $N = 2$ and $N = 4$ increases with U. Increasing N beyond 4 seems to result in a negligible improvement in performance. We observed that for $N > 4$, most of the additional states are essentially obtained by sub-partitioning the best state in the 4-state model. Thus, the modeling accuracy achieved by increasing the number of states beyond four is negligible. However, at smaller values of ρ, the channel will spend more time in the "bad" region, resulting in a finer partitioning of this region, i.e., for $N > 4$ many of the additional states beyond the first four lie in the low SNR region. In this case, the performance gain resulting from increasing N beyond four is more noticeable. We observe similar results for the CIF-Q scheduling algorithm in Figures 3 and 4. Interestingly, the throughput of WFS under the GE model lies between the throughputs that are obtained under $N = 2$ and $N = 4$, i.e., the GE model is more accurate than a 2-state partition-based model. This is not the case for CIF-Q, where the GE model is observed to be less accurate than a partition-based 2-state model (the case $N = 2$). These results suggest that the accuracy of the GE model depends highly on how the scheduling algorithm makes use of the channel information. As the channel conditions deteriorate (ρ becomes smaller), the difference between the GE model and the SNR-based Markov models becomes more pronounced. Therefore, if the scheduling algorithm is designed solely based on GE models, the observed performance can significantly deviate from the forecasted performance.

Figures 5 through 8 depict the performance obtained under different channel models and a 2-state SNR-based prediction model. The purpose of this figure is to demonstrate that the results obtained using 2-state prediction *and* channel models are biased towards the 2-state prediction model. In other words, the 2-state prediction model gives good performance only when the actual channel dynamics follow a 2-state Markov model. In reality, however, channel dynamics are more complex than that, and are more accurately captured by a higher-order Markov model.

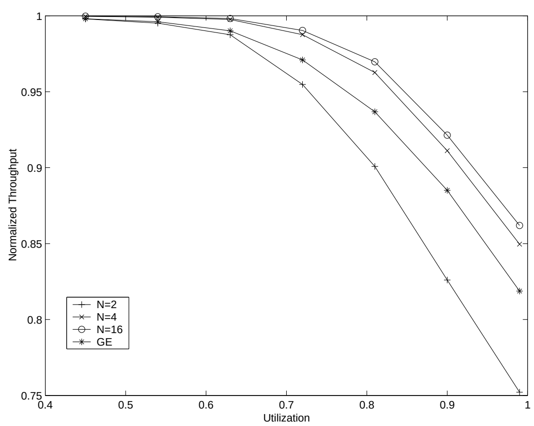

Fig. 1. Impact of prediction model on throughput for WFS.

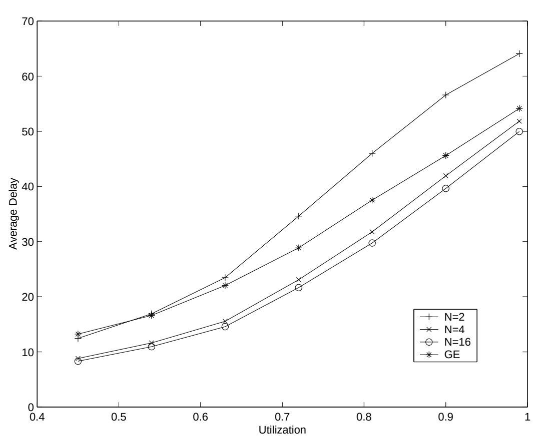

Fig. 2. Impact of prediction model on delay for WFS.

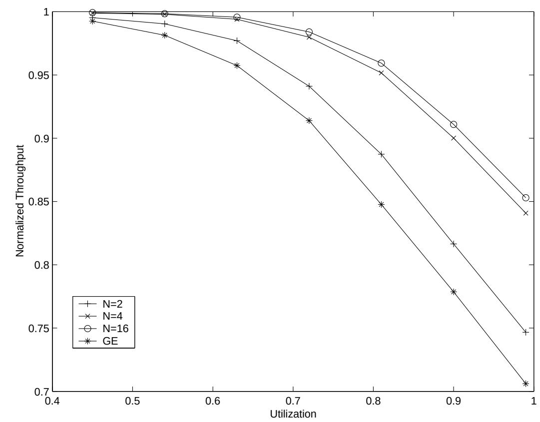

Fig. 3. Impact of prediction model on throughput for CIF-Q.

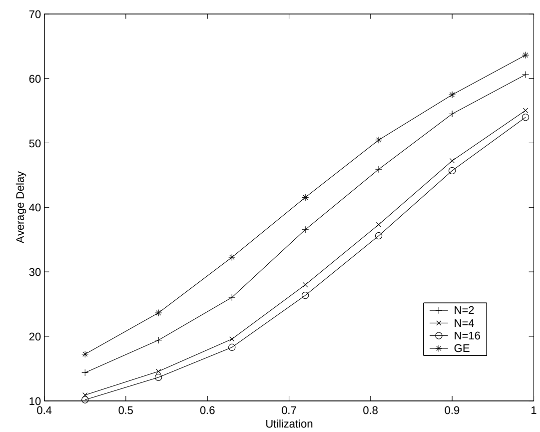

Fig. 4. Impact of prediction model on delay for CIF-Q.

IV. CONCLUSIONS

In this paper, we investigated the impact of channel-state prediction on the achievable throughput and delay performance of two popular wireless scheduling schemes. We observed that when the channel fluctuates according to Jake's model (which is a good approximation of the fading dynamics at the mobile receiver of a cellular system), the throughput improves and the mean delay decreases as N (the number of states in the Markovian predictor) increases. The improvement in throughput is most noticeable when N goes from 2 to 4. In the case of WFS, a 2-state GE model whose parameters are obtained based on Jake's simulator is better than a 2-state model whose parameters are obtained through SNR partitioning. The opposite was observed for CIF-Q. For an SNR-based 2-state prediction model and M-state Markov channel models, the performance degrades with M; i.e., the performance be-

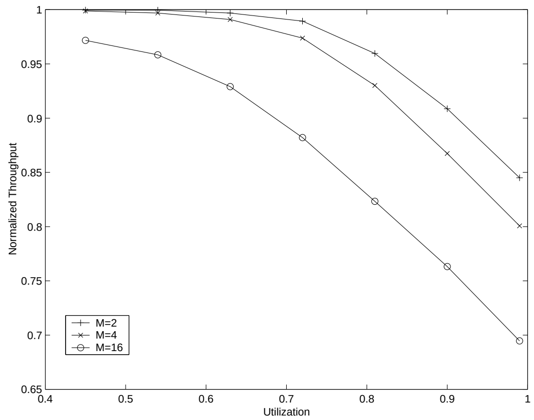

Fig. 5. Impact of channel model on throughput for WFS.

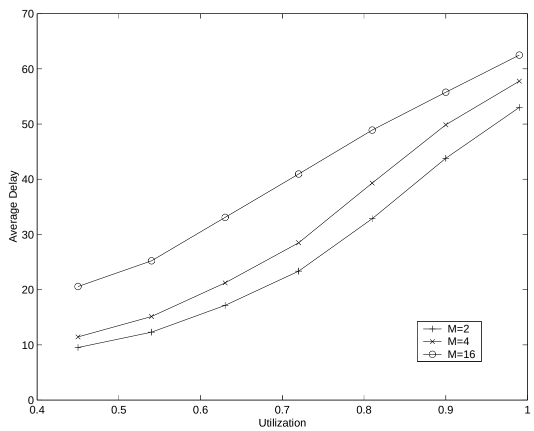

Fig. 6. Impact of channel model on delay for WFS.

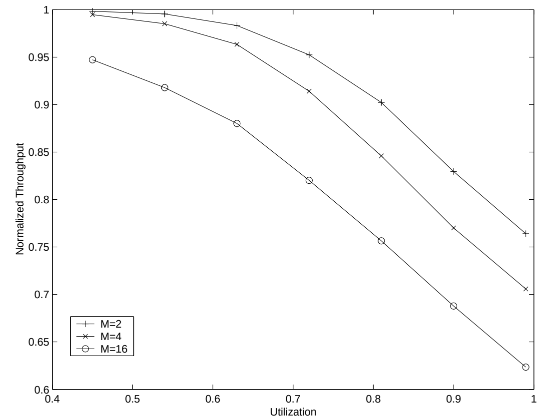

Fig. 7. Impact of channel model on throughput for CIF-Q.

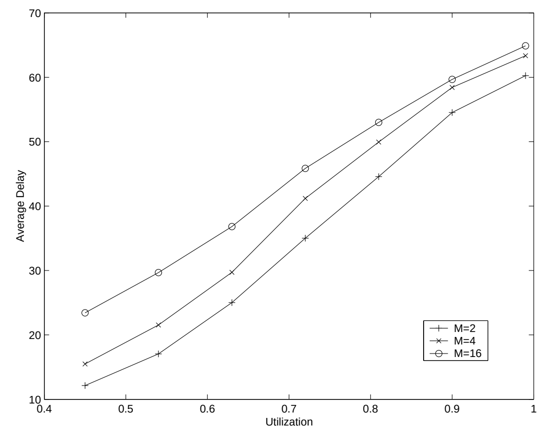

Fig. 8. Impact of channel model on delay for CIF-Q.

comes overly optimistic as *M decreases*. This says that the results obtained in previous wireless scheduling studies under a 2-state predictor and a 2-state channel are optimistic.

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