Channel Adaptive Techniques in the Presence of Channel Prediction Inaccuracy [1]

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Abstract: *Adapting transmission parameters to the future channel state is an appealing approach to improve efficiency in wireless communication. Adaptation requires predicting the channel state. Current channel-adaptive techniques assume that the prediction is perfect. In this paper, we claim that neglecting the prediction error can lead to poor performance results, possibly even worse than without prediction at all.*
We have simulated the behaviour of adaptive modulation and adaptive scheduling, as well as a combination of both for inaccurate channel prediction. The results show that prediction inaccuracy can degrade the performance of wireless communications when channel adaptive techniques are used. The sensitivity to inaccuracy is, however, dependent on several factors, like the adaptive technique used or the average received signal-to-noise level at the receiver.

Keywords: prediction accuracy, channel-adaptive techniques, simulation

1 Introduction

The widespread use of wireless communications has increased performance and reliability requirements. As the wireless channel is a very error-prone medium, error mitigation and control techniques have to be used. However, the error characteristic is time-varying and a static policy leads to low error performance or low resource use. An appropriate solution to mitigate the effects of time-varying errors is to adapt transmission parameters to the channel state.

Such channel adaptive techniques (CAT) — e.g., adapting the used modulation or transmission power or delaying the transmission of packets — assume that information about the *future* channel state exists and is available. In fact, several methods exist which can provide the sender with an estimate or prediction of the channel behaviour (namely, its attenuation) [3, 7]. However, none of these methods is perfect: the prediction results are inaccurate and do not correspond exactly to the future behaviour of the channel [6]. The influence of this inaccuracy on the performance of channel adaptive techniques evidently has a large impact on the suitability of such techniques and should hence be carefully studied — a study that is largely missing so far.

We developed a framework which enables this kind of study for different channel-adaptive techniques and combinations of them [1]. In this paper, we present the results obtained for adaptive modulation and adaptive scheduling [2], as well as the combinations of adaptive scheduling with adaptive modulation. The results show that the impact of prediction inaccuracy has to be carefully taken into account when designing and using CATs.

The rest of the paper is organised as follows: Section 2 describes our approach to capture prediction inaccuracies in a simulation framework; Section 3 discusses the channel adaptive techniques that we investigate. The results of this investigation are presented and discussed in Section 4; Section 5 concludes.

2 Modelling Prediction Inaccuracy

There are a number of different approaches to predict channel behaviour [3, 7]. As all of them are fairly complex and resource-intensive, it would be very difficult and time-consuming to actually implement, e.g., in a simulation model, every existing solution to channel prediction and then evaluate their effects on the channel-adaptive techniques. In particular, simulating such a model with actual prediction algorithms inside would not be feasible at acceptable runtimes and at acceptable levels of statistical confidence. Hence, we use a *model for prediction inaccuracy* instead of the actual prediction algorithms. This model can capture and is adapted to the inaccuracy of a channel predictor, without depending on the prediction algorithms themselves. This prediction model (Section 2.2) is based on an analog channel model (Section 2.1) and is used in the context of a system model (Section 2.2). The resulting simulation framework is described in more detail in [1].

2.1 Channel Model

The channel behaviour is expressed by the attenuation in dB, a_k, at the discrete time instant k. We use a Rayleigh fading channel model to generate a_k. The granularity of the samples depends on the bandwidth of the Rayleigh process and, consequently, on the speed of the receiver (which determines the maximum Doppler frequency).

The value of the attenuation is then used, together with the transmitted signal power and the noise power (both in dBm), which is assumed to be additive, white and Gaussian (AWGN), to calculate the signal to noise ratio (SNR) for each sample. Depending on the used modulation scheme, the received signal-to-noise ratio is converted to energy-per-bit E_b/N; this value is then used to calculate the probability of a bit error, from a curve relating E_b/N to BER for the used modulation [5].

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2.2 Prediction Model

Let a_k be the *actual* attenuation value at discrete time instant k (as computed by the Rayleigh fading model). To model an inaccurate predictor, we have to determine, at a given time k_0 when the prediction algorithm is engaged, the predicted attenuation values $\hat{a_j}$ at j samples in the future from k_0 (i.e., actual values a_k are indexed by absolute time; predicted values $\hat{a_j}$ are indexed by relative time starting from the time the prediction takes place). The *prediction error* is then $e_j = a_k - \hat{a_j}$ where $k = k_0 + j$; it is illustrated in Figure 1. We also assume that the error e_j has mean 0 and follows a Gaussian distribution.

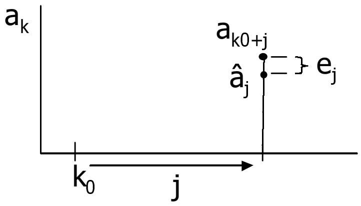

Figure 1: Predicted attenuation value $\hat{a_j}$ and its error, depending on horizon j.

The prediction accuracy $\alpha_j \in (0, 1)$ is then defined as the percentage of predicted values which are within a range β of the real signal value for a fixed prediction horizon j (see Figure 2). I.e., a predictor has accuracy α_j for a time horizon of j samples if $\mathrm{P}(|e_j| < \beta) = \alpha_j$; β is a pre-defined design parameter.

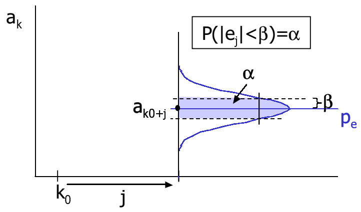

Figure 2: Prediction accuracy as defined by α and β.

2.3 System Model

The system model is shown in Figure 3: We consider two wireless terminals (sender and receiver), communicating only in one direction. A sender sends packets over an error-prone wireless channel with constant bandwidth to a receiver. No MAC protocol is needed as there are only two communicating WTs and only simplex communication is considered.

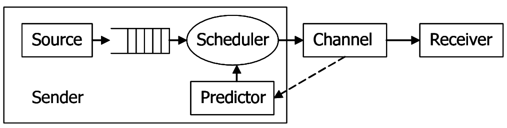

Figure 3: System model

The sender contains the source of packets as well as a scheduler and a predictor module. The scheduler performs the actual channel adaptive transmissions (described in the next section), with the help of the predictor: the scheduler can obtain an estimated attenuation value from the prediction, for any desired prediction horizon j (in fact, for efficiency the predictor returns all relevant sample values for a given packet time). The simulated predictor computes these estimates by using the "actual" attenuation values of the channel model and adding a normally distributed prediction error to it; its variance is determined from α and β (the mean is 0).

3 Channel-adaptive Techniques

Based upon the estimated channel attenuation obtained from the predictor, the scheduler decides how to adapt one or several transmission parameters. The basis of this decision, for all adaptation techniques, is the computation of the expected number of bit errors in a packet: for a given start time and packet length, the *highest* (predicted) attenuation within this packet length is used to determine (using the transmission power) the smallest SNR that this packet will encounter. Based on this SNR, the bit error rate (BER) and the expected number of bit errors is computed. A parameter combination is acceptable (the packet is sent) if this expected number of bit errors is smaller than 1, corresponding to a maximal $\mathrm{BER}_{\max} = 1/\mathrm{packetlength}$. The individual adaptation techniques vary different parameters to ensure such an acceptable combination.

3.1 Adaptive Schedulers

Channel-adaptive schedulers avoid sending data over a channel in a bad condition, i. e. one which would lead to an expected number of errors larger than 1 at the receiver; instead, they simply *wait* for better channel conditions to attempt transmission.

Two simple channel-adaptive schedulers were used to check the degradation suffered from inaccurate channel prediction. The sending time of each packet is adapted to the channel conditions according to one of two scheduling policies.

The *Clairvoyant* scheduler requires the *predicted* channel to be free of errors for the length of the packet. The scheduler postpones the packet until that condition is true and then sends it. This means that the predicted BER for the packet must be lower than or equal to the $\mathrm{BER}_{\max}$ calculated for the packet. The *Clairvoyant Drop at Deadline* scheduler works in a way similar to the Clairvoyant one with the difference that it can postpone the packet only up to the deadline; if the sending condition is not met, the packet is dropped. An example where this scheduler would be useful is real-time traffic where the transmission of a packet is useless after some maximum delay since the packet information has become stale anyway.

Finally, the *Blind* scheduler does not use the channel state information to take decisions. A packet is sent as soon as it arrives at the head of the queue. This algorithm serves as a performance reference.

3.2 Adaptive Modulation

The modulation is also chosen according to the minimum predicted signal value at the receiver. The highest possible modulation is chosen that still leads to a bit error probability lower than $\mathrm{BER}_{\max}$. It is taken into account at the time of the prediction that using a higher modulation reduces the packet duration.

3.3 Adaptive Schedulers with Adaptive Modulation

Both adaptive schedulers are combined with adaptive modulation. This is done by checking, for a certain possible transmission start time, whether the packet can be sent with the highest modulation (BER for the packet is lower than $\mathrm{BER}_{\max}$). If not, the second highest modulation will be tried for the same start time, and so on. If a packet cannot be sent even using the lowest available modulation at a time, then the next possible transmission start time will be tried. This process repeats itself until a start time is found for which the send condition $\mathrm{BER} \leq \mathrm{BER}_{\max}$ is met.

4 Results

4.1 Parameters

A Rayleigh fading channel was generated deterministically using Jakes's sum of cosines method [4] at 2.4 GHz, with a maximum Doppler speed of 6 km/h (the coherence time is 16,88 ms). All results shown here were obtained for an average SNR of 9 dB at the receiver. The channel has a raw capacity of 2 Mbps when the lowest modulation is used.

The load was CBR with 4000 bit packets. Load is varied solely by varying the interval between the generation of two packets. A MAC header of 272 bits (802.11) was added to the packets, which is always transmitted with the lowest possible modulation (BPSK in this case). It is taken into account when making the prediction. A physical layer header of 192 bits (802.11b) was also used, which is not taken into account either when making the prediction or at the reception. It is used only to model the overhead in transmission time.

Each simulation run was 500 s long. The modulation could be chosen among BPSK, 4-PSK, 8-PSK, 16-PSK, 32-PSK and 64-PSK. When the modulation is not adapted, BPSK is used.

4.2 Metrics

The metric used to evaluate the performance is the packet delivery rate, i.e., the ratio of correctly received packets to all generated packets in 500 s. Since a MAC and PHY overhead of 11.6% is added to every packet, at 100% load more load is offered to the channel than it can actually transmit when using the lowest modulation. This implies that the maximum packet delivery rate at 100% load is 0.888 and not 1. This load level has been chosen to highlight the benefits of adaptive modulation.

4.3 Simple Adaptive Mechanisms

Figure 4 shows the improvements in packet delivery rate achieved using channel-adaptive scheduling and adaptive modulation or a combination of both for 100% load. For the Clairvoyant Drop at Deadline scheduler deadlines of 10 ms and 40 ms were used, one shorter and one much longer than the channel's coherence time (16,88 ms). Since 100% load is used here, changing the deadline for Clairvoyant Drop scheduler does not significantly influence the packet delivery rate: for short deadlines more packets are dropped by the scheduler because of lack of error-free transmission start time; for long deadlines more packets are dropped in the queue while the scheduler is busy waiting until a farther transmission start time for the packet at the head of queue.

Due to the low average SNR at the receiver, the channel-adaptive schedulers do not deliver any packets for high modulations (an error-free transmission start time can never be found). Adaptive modulation alone achieves a high performance, which confirms the efficiency of this CAT. Its combination with adaptive scheduling further improves the performance, achieving the highest packet delivery rate.

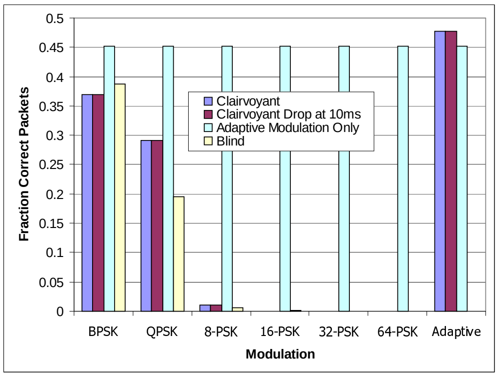

Figure 4: Fraction of correctly delivered packets for channel-adaptive schedulers with different static modulations and for their combination with adaptive modulation. Average noise power of 6 dB at the receiver.

Figure 5 shows the packet delivery rate for each of the adaptive mechanisms working alone. One can see that the adaptive mechanisms used alone are quite stable against the inaccurate prediction in the simulated range. Only for $\beta = 5$ dBm do the adaptive schedulers and adaptive modulation show a small reduction in the packet delivery rate.

We ran several simulations for different values of the average SNR at the receiver. It turned out that the results depend, for the adaptive schedulers, on the difference between the average received SNR and the $\mathrm{SNR}_{\min}$ which corresponds to the limit $\mathrm{BER}_{\max}$ for the packet. The reason is intuitive: if the average channel attenuation is near the threshold value to send the packet, even small prediction errors can lead to taking the false decision (postponing the packet although the channel is good or sending even when the channel is bad). This necessarily leads to a higher number of channel errors for sending at bad times, and longer waiting times for postponing when the channel is good; both these effects lead to a lower fraction of correctly delivered packets. In a realistic scenario, the average SNR changes with time due to propagation phenomena other than Rayleigh fading, like shadowing. This means that the average received SNR changes with time. The adaptive schedulers will then perform worse at times when it is around the threshold value. Adaptive modulation does not suffer from this effect, since the BER thresholds of a packet change due to the change of the modulation.

4.4 Combined Adaptive Mechanisms

In Figure 6, the variation in fraction of correctly received packets is plotted for the different combinations of CAT. In every case the amount of data which could be correctly received decreases. This indicates that prediction inaccuracy has a stronger influence on the performance of combined adaptive techniques than it does on each one for itself.

5 Conclusions

We tested the sensitivity of channel-adptive schedulers and channel-adaptive modulation to inaccuracy in channel prediction using a simulation framework developed for the purpose. The results show that inaccurate prediction of channel attenuation only slightly affects the channel-adaptive schedulers and adaptive modulation. For the first mechanism, however, a stronger reduction in the fraction of correctly delivered data can be seen when the average SNR at the receiver lies close to the threshold BER. This effect is not seen for adaptive modulation. We also looked into the combination of channel-adaptive scheduling with adaptive modulation. The results show that the combination of the two different CATs is more sensitive to prediction inaccuracy, and the performance is then worse than that of the simple scheduler for the same value of prediction inaccuracy.

These results lead, as expected, to the conclusion that, although CAT are a good means to improve the performance of wireless communication, their performance depends on the accuracy of the prediction algorithms used. Furthermore, combination of more than one CAT can increase the sensitivity to inaccuracy. In particular this last results warrants additional future work in finding CAT combinations that are robust to prediction inaccuracy.

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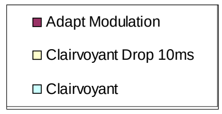
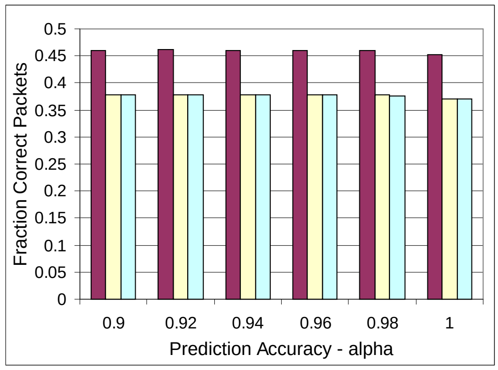
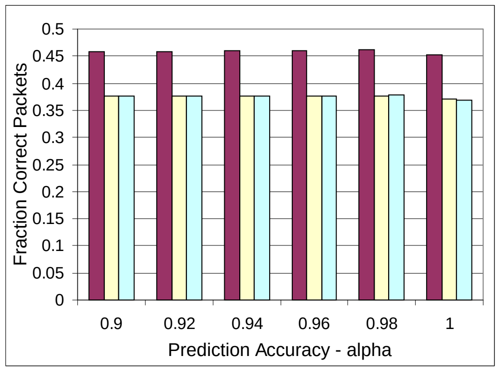


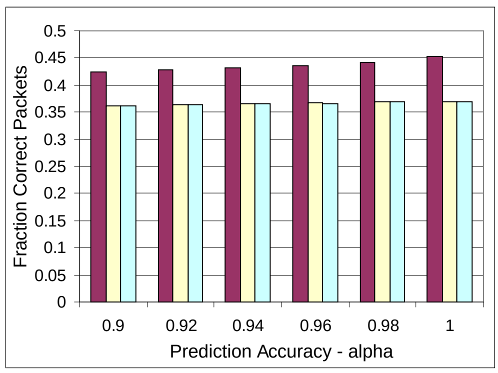
(a) Legend



(b) $\beta = 1$ dB

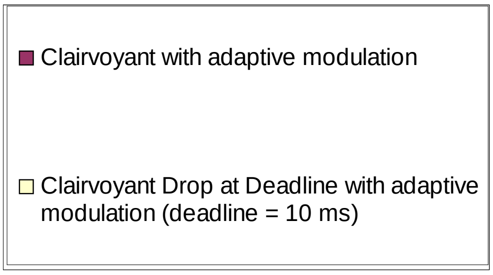


(c) $\beta = 2$ dB



(d) $\beta = 5$ dB

Figure 5: Fraction of correctly delivered packets as a function of the prediction accuracy α for $\beta = 1, 2, 5dB$. Average noise power of 6 dB at the receiver.



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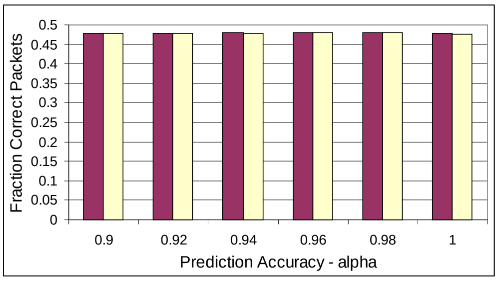
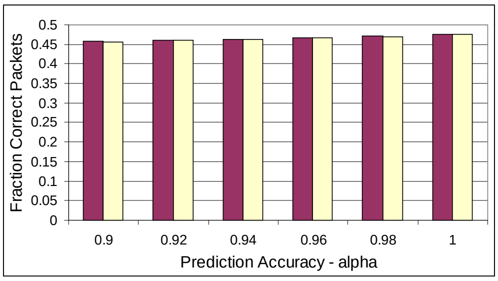
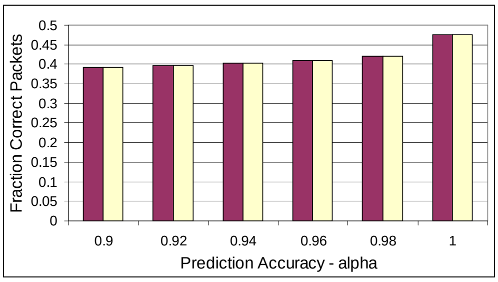


(b) $\beta = 1$ dB



(c) $\beta = 2$ dB



(d) $\beta = 5$ dB

Figure 6: Fraction of correctly delivered packets as a function of the prediction accuracy α for $\beta = 1, 2, 5dB$. Average noise power of 6 dB at the receiver.

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