University of Waterloo
Coding & Signal Transmission Laboratory
Department of Electrical & Computer Engineering
Waterloo, Ontario, Canada, N2L 3G1
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James Yang, Amir K. Khandani, and Noel Tin

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James Yang†, Amir K. Khandani†, and Noel Tin‡
†Coding & Signal Transmission Laboratory(www.cst.uwaterloo.ca)
Dept. of Elec. and Comp. Eng., University of Waterloo, Waterloo, ON, Canada, N2L 3G1
e-mail: james, khandani@cst.uwaterloo.ca, Tel: 519-884-8552, Fax: 519-888-4338
‡Bell Mobility, 5099 Creekbank Road, 5N, Mississauga, ON, Canada, L4W 5N2
e-mail: noeltin@Mobility.com, Tel: 905-282-4725, Fax: 905-282-3337

Abstract

In this paper [1], we address the application of Adaptive Modulation and Coding (AMC) for 3rd-Generation (3G) wireless systems. We propose a new method for selecting the appropriate Modulation and Coding Scheme (MCS) according to the estimated channel condition. In this method, we take a statistical decision making approach to maximize the average throughput while maintaining an acceptable Frame Error Rate (FER). We use a first-order finite-state Markov model to represent the average channel Signal-to-Noise Ratio (SNR) in subsequent frames. The MCS is selected in each state of this Markov model (among the choices proposed in the 3G standards) to maximize the statistical average of the throughput in that state. Using this decision-making approach, we also propose a simplified Markov model with fewer parameters, which is suitable in systems where changes in the fading characteristics need to be accounted for in an adaptive fashion. Numerical results are presented showing that both of our models substantially outperform the conventional techniques that use a *threshold-based* decision making.

Index Terms

Adaptive Modulation and Coding, Spectral Efficiency, Turbo Coding, Lognormal Shadowing, First-Order Finite-State Markov Model, 3rd-Generation Code Division Multiple Access (CDMA).

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I. INTRODUCTION

The use of Adaptive Modulation and Coding (AMC) is one of the key enabling techniques in the standards for 3rd-Generation (3G) wireless systems that have been developed to achieve high spectral efficiency on fading channels [1]–[4]. The core idea of AMC is to dynamically change the Modulation and Coding Scheme (MCS) in subsequent frames with the objective of adapting the overall spectral efficiency to the channel condition. The decision about selecting the appropriate MCS is performed at the receiver side according to the observed channel condition with the information fed back to the transmitter in each frame. Many AMC techniques have been presented in the literature. In the following, we provide a brief description of some of these papers that are more relevant to this current article. Readers are referred to [5] for a more detailed list of references on this topic.

In [6] and [7], various rate and power adaptation schemes are investigated. The power adaptation policy found is essentially a water-filling formula in time. In [7], a variable-power variable-rate modulation scheme using M-ary Quadrature Amplitude Modulation (MQAM) is proposed. The presented results show that the proposed technique provides a 5–10 dB gain over variable-rate fixed-power modulation using channel inversion and truncated channel inversion (where the received power is maintained constant), and up to 20 dB gain over the nonadaptive modulation.

In [8], the channel capacity of various adaptive transmission techniques is examined. The performance of these techniques employed with space diversity are also investigated. It is shown that the spectral efficiency for a fading channel can be improved by adaptive transmission techniques in conjunction with space diversity. It is also found that when the transmission rate is varied continuously according to the channel condition, varying the transmit power at the same time has minimal impact.

In [9], the adaptation technique from [6] and [7] is modified to take into account the effect of constrained peak power. Simulation results show that with a reasonable peak power constraint, there is a small loss in spectral efficiency as compared to the unconstrained case.

In [10], an AMC scheme is proposed based on the variable-power variable-rate technique from [6] and [7]. This technique superimposes a trellis code on top of the uncoded modulation. Simulation results show that with a simple four-state trellis code, an effective coding gain of 3 dB can be realized.

In [11], a variable rate adaptive trellis-coded QAM is discussed, offering lower average Bit Error Rate (BER) as compared to fixed rate schemes.

In [12], another AMC technique is proposed using M-ary Phase-Shift Keying (MPSK) modulation, which offers 3–20 dB gain in BER performance.

In [13], another AMC scheme is proposed which utilizes a set of trellis-codes originally designed for Additive White Gaussian Noise (AWGN) channels. This scheme is applied to a model of fully loaded microcellular network for spectral efficiency comparisons against nonadaptive coded modulation. The obtained results show that the AMC schemes provide significant advantages over a traditional nonadaptive coded modulation scheme in terms of the average spectral efficiency and decoding delay.

Turbo Codes [14], which can achieve near-capacity performance on AWGN channels, have also been proposed in adaptive transmission systems to further improve performance [15]. Results show that a gain of about 3 dB can be obtained over an AMC scheme using trellis coded modulation.

For packet data in the 3G standards, Turbo Codes are specified as the channel coding technique; throughout this paper, we follow the guidelines provided in the standards. The MCS's considered include 16QAM with Turbo Code rate $R_c = 1/2$, 8PSK with $R_c = 1/2$, and BPSK with $R_c = 1/3$, where all of these MCS's have equal average symbol energy, E_s. Data is transmitted in successive frames. Each frame of bits has a constant duration of 5 ms, and consists of 384 coded symbols. This provides a constant data rate of 76.8 ksymbols/s regardless of the choice of MCS [1]–[4].

A key factor determining the performance of an AMC scheme is the method used at the receiver to estimate the channel condition and thereby deciding for the appropriate MCS to be used in the next frame. The performance of Turbo Code in AMC systems depends heavily on the accurate prediction of the channel condition, which is usually a difficult task given the time-varying nature of the mobile environment. This is due to the fact that Turbo Codes operate close to the channel capacity and thus have steep performance curves. The sensitivity of Turbo Codes to prediction errors may cause the system to produce much less favorable results than expected. With much of the industry interest in 3G development, it is essential to overcome this shortcoming and find methods for using Turbo Codes in AMC systems under a more realistic environment, where prediction errors can often occur.

In the literature, many articles present AMC schemes without considering the effect of prediction errors in decision making. However, some of these references study the effect of such errors on resulting performance. This is the case with [7], where the effect of channel estimation errors is addressed for the first time. In some other articles, authors have employed more sophisticated predictors to improve the prediction accuracy. An example is reference [11], where the proposed scheme uses pilot symbols to estimate channel state at the receiver, and utilizes both an interpolation filter and a linear prediction filter to interpolate and predict channel conditions, respectively.

In some other references, authors have included the effect of prediction errors in the decision making. For example, in [16], the effect of fading channel variations is formally addressed, where the definition of strongly robust signaling is introduced. This is based on the idea of designing an adaptive signaling scheme such that it meets the BER requirements for a set of fading autocorrelation functions. This idea is applied to both uncoded modulation as well as trellis-coded modulation. Results show that the proposed schemes provide significant improvement in BER and rate in bits per symbol over the scheme that assumes a static channel.

In most works [6]–[13], [15], [16], the decision of which MCS to use for the next frame is based on the basic idea of partitioning the estimated channel Signal-to-Noise Ratio (SNR) into regions using a set of threshold values. Each such region is associated with a particular MCS while the threshold values are optimized to maximize the overall throughput. In this paper, we propose a new method for selecting MCS with the objective of maximizing the statistical average of the channel throughput when there may exist an error in predicting the channel SNR. A simplified model with fewer parameters is also proposed, which can be used to account for the changes in the fading characteristics by updating the model parameters in an adaptive manner. Numerical results show that our method outperforms the conventional *threshold* method.

The remainder of this paper is organized as follows. In the next section, we describe our system setup and channel model. In Section III, we discuss the conventional *threshold* method and its shortcomings. Our proposed method is presented in Section IV. Numerical results are presented in Section V, including throughput comparisons between the *threshold* method and our proposed method, as well as results obtained from some studies on the robustness of our proposed model. Finally, we conclude in Section VI.

II. System Setup and Channel Model

For our channel model, we consider a fading channel with time-varying lognormal-distributed complex gain, λ_k, and additive white Gaussian noise. This is similar to the model used in several other related papers including [7] and [10]. The lognormal complex gain represents the lognormal shadowing effect in the channel and is implemented by the following autoregressive model [17]

$$R(\tau) = e^{-v|\tau|/d}, \tag{1}$$

where v is the speed of the vehicle, τ is the sampling period, and d is the effective decorrelation distance. This distance is in the order of 10–100 m as reported in [18].

Using (1), the lognormal values can be generated by low-pass filtering of a discrete white Gaussian random process. With this model, we have [17]

$$\lambda_{k+1} = \xi\lambda_k + (1-\xi)\theta_k, \tag{2}$$

where λ_k is the mean fading level (in dB) that is experienced at location k, ξ is a parameter that controls the spatial correlation of the lognormal shadowing, and θ_k is a zero-mean Gaussian random variable, which is independent of λ_k.

The variance of θ_k, σ_θ^2, is related to the variance of the lognormal shadowing, σ_λ^2, and the parameter, ξ, through [17]

$$\sigma_\lambda^2 = \frac{1-\xi}{1+\xi}\sigma_\theta^2. \tag{3}$$

By selecting appropriate values for σ_λ^2 and ξ, lognormal shadowing with any desired standard deviation and spatial correlation can be generated. In our simulations, we have chosen values for these parameters such that the correlation between subsequent fading values follow the results reported in [18] for reasonable values of vehicle speed. Note that a different fading value is generated for each symbol of duration 13μs (a frame of 384 symbols corresponds to 5 ms resulting in a symbol duration of 13μs).

In this paper, we follow the guidelines provided in the 3G standards in terms of modulation schemes, code rates, and frame structure as outlined in the last section. Each coded symbol in a frame has a different lognormal gain, λ_k, generated by (2), and the channel SNR of a coded symbol is defined, in decibel scale, as

$$\gamma = \lambda_k + 10\log\left(\frac{E_s}{N_o}\right), \tag{4}$$

where N_o is the one-sided noise spectral density, E_s is the average symbol energy, and λ_k is as defined in (3). The per frame average channel SNR, which is the basis of the MCS selection criterion for the subsequent frame, is the average of the channel SNR of all the coded symbols in the frame.

It is assumed that the average channel SNR is accurately estimated at the receiver and that no delay or transmission errors can occur in the feedback channel, so any discrepancy between the predicted and the actual SNR of the next frame can only result from channel SNR prediction errors caused by the time-varying nature of the channel.

The performance criterion used for evaluation of the *threshold* method and our proposed method is the statistical average of throughput per transmitted frame. This is determined by the corresponding probability of Frame Error Rate (FER) and the spectral efficiency of the MCS selected in the frame. The use of FER for determining throughput instead of BER is due the fact that if errors are detected in a frame after decoding, the entire frame is retransmitted and thus any correctly decoded bits in that frame should not be included in the average throughput calculation.

III. Threshold Method

Conventionally, in what we call the *threshold* method, the AMC system has a set $\{M_0, \ldots, M_{n-1}\}$ of n MCS's. This MCS set has a corresponding throughput versus average channel SNR, denoted by $\{T_i(\gamma), i=0, \ldots, n-1\}$, where γ is the per-frame average channel SNR as defined earlier. These throughput values can be graphically represented, where the curves intersect with each other. The average channel SNR values corresponding to the intersection points are chosen as the threshold values, denoted by $\{\gamma_0 = -\infty, \gamma_1, \ldots, \gamma_{n-1}, \gamma_n = \infty\}$. These threshold points partition the range of SNR into n regions, denoted by $[\gamma_i, \gamma_{i+1})$ for $i=0, \ldots, n-1$. The kth MCS, namely M_k, is assigned to the region $[\gamma_i, \gamma_{i+1})$ if the following condition is satisfied

$$T_k(\gamma) \geq T_j(\gamma), \quad \forall\, j \neq k,\ \forall\, \gamma \subset [\gamma_i, \gamma_{i+1}). \tag{5}$$

With this correspondence between the MCS's and the channel SNR, M_k is selected for the next frame if the average channel SNR in the current frame lies in the region $[\gamma_i, \gamma_{i+1})$.

Since it is assumed in the *threshold* method that the fading is slow enough such that the average channel SNR remains in the same region from the current frame to the next, the estimated channel SNR of the current frame is simply taken as the predicted channel SNR for the next frame. This simplifying assumption, however, is often not true in a mobile environment. In such a case, an error in the estimation of average channel SNR can cause inappropriate selection of MCS, resulting in a degradation in FER performance.

As mentioned, Turbo Codes are specified as the channel coding technique for packet data in the 3G standards. One of the main characteristics of Turbo Codes is that they operate close to the channel capacity and the corresponding FER vs. SNR curves have a steep slope (Figure 1). This means that even a small prediction error in channel SNR can result in a large degradation in FER. Therefore, it is essential to take into account the possible prediction errors when designing an AMC system where Turbo Codes are employed.

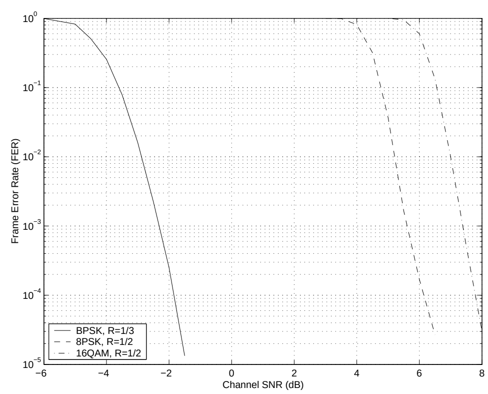

Fig. 1. FER vs. SNR for Turbo Coded modulation schemes

IV. Markov Model

We consider a first-order finite-state Markov model to represent the time variations in the average channel SNR. The states in this model represent the average channel SNR of a frame uniformly quantized in dB scale with a given step size Δ, and they form a set $\{S_0, \ldots, S_{m-1}\}$ of m states.

As in the *threshold* method, assume that there are n MCS's. We denote N_i as the number of information bits in a frame of 384 coded symbols that uses the ith MCS, namely M_i. Table I shows the values of N_i for the three MCS's used in this paper as specified in the 3G standards. We also define F_{ij} as the FER of M_i in state j, and T_{ij} as the expected throughput of M_i in state j.

TABLE I

VALUES OF N_i FOR THE THREE MCS'S USED IN THE 3G STANDARDS

Modulation Scheme, $M_i, i=0,1,2$	Turbo Code Rate, R_c	Number of information bits, N_i
16QAM	$1/2$	768
8PSK	$1/2$	576
BPSK	$1/3$	128

In the following, we propose a method for selecting the appropriate MCS based on the states of a first-order Markov model, and evaluate its expected throughput. The basic strategy is to assign an MCS to each state such that the expected throughput is maximized in that state.

A. Full-Scale Model

We simulate a channel with lognormal shadowing according to (1)–(3) where the average SNR corresponding to each frame is uniformly quantized with a given step size Δ. We have selected appropriate values for ξ and σ_λ^2 in (1)–(3) such that the correlation between subsequent fading values follow the results reported in [18] for reasonable values of vehicle speed (a different fading value is generated for each symbol of duration 13μs.) An appropriate offset is added to the fading values so that they result in an acceptable FER performance.

The calculation of the expected throughput for each MCS in each state of the Markov model requires the knowledge of the corresponding transitional probabilities. For a given number of states, m, and a given Δ, the transitional probabilities can be obtained by simulating the transmissions of a large number of frames of bits. These transitional probabilities form a set $\{P_{ij},\, 0 < i, j < m-1\}$, where P_{ij} is the transitional probability from state i to state j.

The stationary probabilities of the states, denoted by $\{\Pi_j,\, 0 < j < m-1\}$, can be computed using the following well-known system of equations

$$\Pi_j = \sum_{i=0}^{m-1} \Pi_i P_{ij},\ 0 \le j \le m-1, \quad \sum_{j=0}^{m-1} \Pi_j = 1. \tag{6}$$

The expected throughput of M_i in state j, namely T_{ij}, is therefore

$$T_{ij} = \sum_{k=0}^{m-1} N_i P_{jk}(1 - F_{ik}), \tag{7}$$

where N_i is the number of information bits in a frame of 384 coded symbols using the ith MCS, P_{jk} is the transitional probability from state j to state k, and $(1 - F_{ik})$ is the probability of correct transmission if the ith MCS is selected when the Markov chain is in state k.

For each state, we assign the MCS that has the highest expected throughput in that state according to (7) and select this MCS for the next frame if the estimated channel SNR falls in this state. In other words, M_i is assigned to S_j, if

$$T_{ij} \ge T_{kj}, \quad \forall\, k \ne i. \tag{8}$$

We denote the expected throughput in state j as $\overline{T_j}$. The expected throughput averaged over all states is computed using

$$\sum_{j=0}^{m-1} \Pi_j \overline{T_j}. \tag{9}$$

B. Simplified Model

A drawback of the *full-scale* model is that it involves many parameters (m^2 transitional probabilities), and consequently, it is difficult to train the model on the fly to adapt to the changes in the fading characteristics (for example, caused by the variations in vehicle speed). To accommodate such an adaptation, we need a simplified Markov model with fewer parameters, which allows us to dynamically recalculate the transitional probabilities over a window of past symbols of a reasonable size.

As in the *full-scale* model, the set $\{S_0, \ldots, S_{m-1}\}$ represents the m states in the simplified model with a step size Δ between neighboring states. We assume that the connectivities between states are as shown in Figure 2, where

1) The maximum number of transitions from a given state is determined by $r = 2l + 1$, where $r \le m$.
2) $\alpha = \min\{m-1, j+l\}$ reflecting the fact that states above S_{m-1} do not exist; transition probabilities to those states are added to the transition probability to S_{m-1}.
3) $\beta = \max\{0, j-l\}$ reflecting the fact that states below S_0 do not exist; transition probabilities to those states are added to the transition probability to S_0.
4) The transitional probabilities are averaged over all states, and consequently are independent of the state index.

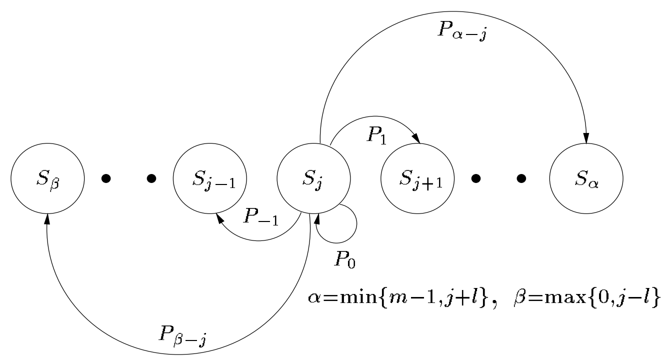

Fig. 2. Simplified Markov Model

The transitional probabilities in the simplified model are specified by $\mathbf{P} = \{P_a, -l \le a \le l\}$. Note that the transitional probabilties exist in pairs, and this allows us to set P_a equal to P_{-a}, where $0 \le a \le l$, further reducing the number of parameters in the model. We have obeserved (through numerical simulations) that in the *full-scale* model these probabilities are almost equal.

The calculation of expected throughput in each state follows a relation similar to (7), slightly modified according to the structure of the simplified model shown in Figure 2.

Since the average and approximated probabilities are now used instead of the true probabilities, this model is expected to yield smaller throughput than the full-scale Model. However, as will be seen in our numerical results, a very good performance can be achieved (at an appropriate step size) while substantially reducing the number of parameters in the model.

As there are fewer parameters in this simplified model (maximum of m transitional probabilities in $\mathbf{P}$), it requires a window of past symbols of a much smaller size for on-the-fly adaptation to the changes in the fading characteristics.

We call this model the *simplified* model with parameters $\{\mathbf{P}, r, \Delta\}$.

C. Robustness of Simplified Model

Setting P_a to equal to P_{-a} and/or using a smaller window size of past frames results in approximation errors in the computation of the transitional probability set, $\mathbf{P}$. Since the MCS is selected from a finite set of candidates, a small error in the transitional probability values does not necessarily result in selecting a sub-optimal MCS. The robustness of the Simplfied Model is, therefore, determined by how much error in the transitional probability values can be tolerated before a sub-optimal MCS is selected.

Assuming that P_a is set to equal to P_{-a}, then the elements of $\mathbf{P}$ is the set $\{P_a, a=0,\ldots,l\}$. Suppose that the corresponding approximation errors are denoted by $\{\epsilon_a, a=0,\ldots,l\}$. Then, the approximated $\mathbf{P}$ is $\{P_a+\epsilon_a, a=0,\ldots,l\}$. Note that since $\{P_a+\epsilon_a, a=0,\ldots,l\}$ is a probability set, the following holds

1) $\sum_a \epsilon_a = 0$,
2) $0 \leq P_a + \epsilon_a \leq 1$.

Suppose that for the jth state, S_j, the two MCS's that offer the highest expected throughput based on $\mathbf{P}$ are M_i and M_k, where $T_{ij} > T_{kj}$, meaning M_i is selected for S_j. The difference between these two expected throughput is equal to $T_{ij} - T_{kj}$. Using $\{P_a+\epsilon_a, a=0,\ldots,l\}$ in a relation similar to (7) (modified according to the structure of the simplified model), we can easily find the change in $T_{ij}-T_{kj}$ due to an error $\{\epsilon_a, a=0,\ldots,l\}$ as follows

$$\delta(T_{ij}-T_{kj}) = \sum_a \epsilon_a K_a, \tag{10}$$

where $K_a = N_i(1-F_{ij+a}) - N_k(1-F_{kj+a})$, denotes the difference between the expected throughput of M_i and M_k in state $j+a$.

Therefore, we can readily identify all the $\{\epsilon_a, a=0,\ldots,l\}$ that decreases $T_{ij}-T_{kj}$ such that it results in $T_{ij}-T_{kj}=0$, beyond which point $T_{kj} > T_{ij}$, meaning a sub-optimal MCS, M_k, will be selected instead of M_i.

D. Algorithm for Implementation of Simplified Model

The goals of using the *simplified* model is to take into account the changes in fading characteristics of the mobile channel. Such a model with parameters $\{\mathbf{P}, r, \Delta\}$ can be implemented using the following algorithm:

1) Throughput versus SNR curves are obtained for each MCS (offline). An example of such curves is shown in Figure 1.
2) Enough number of frames are passed through the channel with the average SNR recorded for each frame.
3) The average SNR values are uniformly quantized based on a given step size, Δ, to set up a first-order finite-state Markov model of m states.
4) The transitional probability set $\mathbf{P}$ of the Markov model is computed based on a given r.
    a) Set $P_a = P_{-a}$ (optional).
    b) The transitions which are not allowed are deleted, and the corresponding P_a's are modified as explained earlier.
5) The expected throughput in each state of the Markov model for each MCS is calculated using a relation similar to (7), modified according to the structure of the simplified model.
6) MCS's are assigned to each of the states in the Markov model according to (8).
7) Steps 2)–6) are repeated over an appropriate time interval for the adaptive case.

V. Results and Discussions

A. Performance of Full-Scale and Simplified Models

The expected throughput per frame computed using (7) and (9) for both the *threshold* method and our proposed method based on the *full-scale* model and the *simplified* model are shown in Figures 3–5 for various Δ, r, ξ (corresponding to different fading characteristics), as well as different average received symbol to noise ratio, $\frac{E_s}{N_o}$ as defined in Section II. The value of Δ determines the number of states in the model. A typical value for the number of states is in the order of 10–20.

From Figures 3–5, it can be seen that both the *full-scale* model and the *simplified* model outperform the *threshold* method. These results, therefore, prove that our proposed method accomplishes the goal of capturing the transitional behavior of the average channel SNR that is lacking in the *threshold* method and in doing so it increases the average throughput.

Referring to Figures 3–5, for both the *full-scale* model and the *threshold* method, the expected throughput reaches a saturation point at approximately $\Delta = 0.5$ dB, below which it stays relatively constant. It is observed that the *simplified* model also reaches this saturation point (corresponding to $\Delta = 0.5$ dB) when $r = m$. When $r \ll m$, the maximum expected throughput occurs at step size of 1 dB, below which the expected throughput decreases as Δ decreases due to the fact that when $r \ll m$, using a smaller Δ means a bigger portion of state transitions is ignored. In particular, when $r = 3$ and $\Delta < 0.2$ dB, the *simplified* model yields the same throughput as the *threshold* method.

It is easy to observe from Figures 3–5 that by setting $\Delta = 1$ dB and $r = 7$ in the *simplified* model, we can achieve a throughput that is very close to the maximum value while using much fewer parameters than needed in the *full-scale* model. Note that the value of m does not affect the implementation complexity of the model, while the value of r determines the window size of past symbols for on-the-fly adaptation.

Numerical results show that for the case of $P_a = P_{-a}$, $\Delta = 1$ dB and $r = 7$, using a window of 500 past frames (corresponding to 2.5 s) to recompute the transitional probabilities results in only 0.5% loss in the expected throughput as compared to using 100000 past frames for this purpose. This shows that the *simplified* model can be easily adapted to the changes in the fading characteristics with a reasonable delay.

As an example, Table II shows the expected throughput of the three MCS's in each state of the *simplified* model along with the resultant MCS assignments for each state when $\xi = 0.999$, $\frac{E_s}{N_o} = 6.75$ dB, $r = 7$ and $\Delta = 1$ dB. It also shows a comparison between the MCS assignments made by the *simplified* model and the *threshold* method. As shown, in some states, the MCS assignments made by these two methods are the same while in other states they are different.

B. Effects of Approximation Errors on the Robustness of the Simplified Model

In the following, we use a simple example (based on some simplifying assumptions) as an indication that the proposed scheme has some degree of robustness against possible errors in the calculation of the transitional probabilities.

Since it is suggested in the last section that the appropriate selection for Δ and r in the *simplified* model are $\Delta = 1$ dB and $r = 7$, in the following, we examine the effect of approximation errors (due to using a smaller window size of past frames for calculating $\mathbf{P}$ and/or setting $P_a = P_{-a}$) on the overall expected throughput for this particular case.

As can be seen in Table II, the difference between the two highest calculated expected throughput in state 8 is the smallest among all the states (8PSK with $R_c = 1/2$ is selected over 16QAM

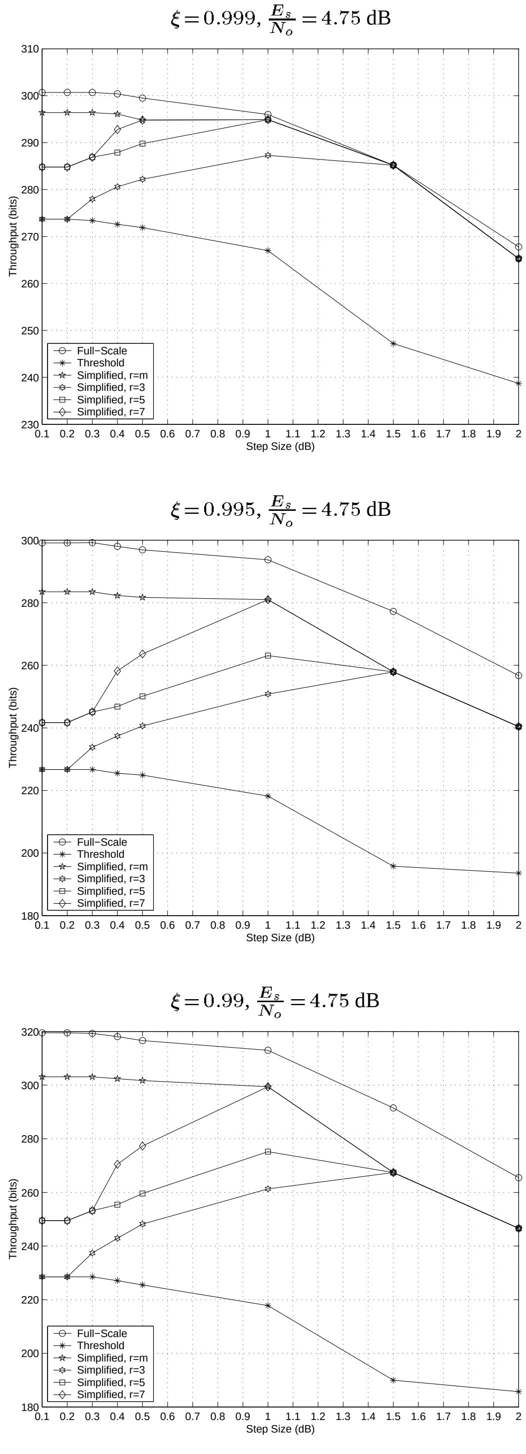

Fig. 3. Throughput vs. Step Size for $\xi = 0.999$, $\xi = 0.995$, $\xi = 0.99$, and $\frac{E_s}{N_o}$=4.75 dB (note that for the *simplified* model $P_a \neq P_{-a}$)

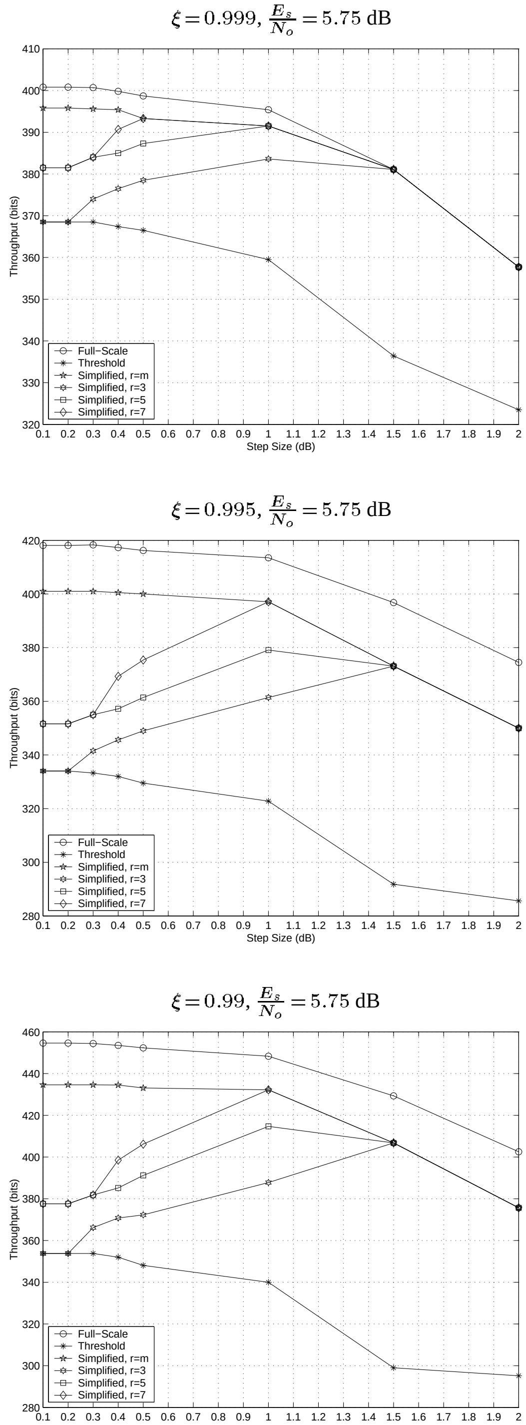

Fig. 4. Throughput vs. Step Size for $\xi = 0.999$, $\xi = 0.995$, $\xi = 0.99$, and $\frac{E_s}{N_o}$=5.75 dB (note that for the *simplified* model $P_a \neq P_{-a}$)

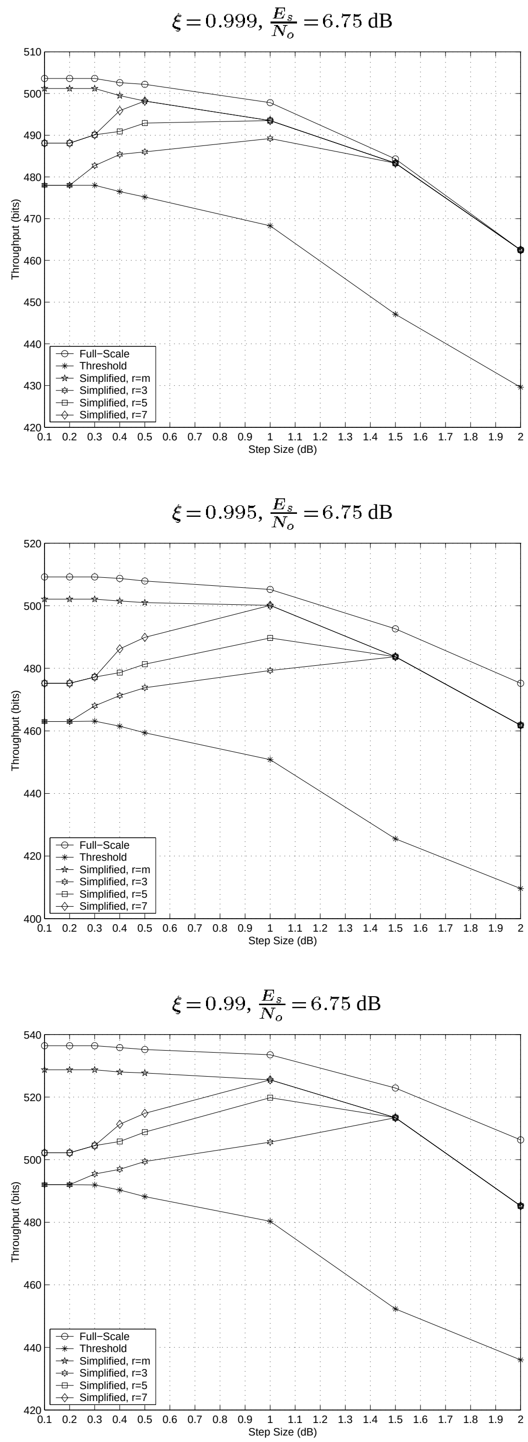

Fig. 5. Throughput vs. Step Size for $\xi = 0.999$, $\xi = 0.995$, $\xi = 0.99$, and $\frac{E_s}{N_o} = 6.75$ dB (note that for the *simplified* model $P_a \neq P_{-a}$)

TABLE II

MCS ASSIGNMENT FOR $\xi = 0.999$, $\frac{E_s}{N_o}$ =6.75 dB USING SIMPLIFIED MODEL AND THRESHOLD METHOD

States, S_j	Expected Throughput, T_{ij} (bits)			MCS Assignment	
	BPSK $R_c = 1/3$	8PSK $R_c = 1/2$	16QAM $R_c = 1/2$	Simplified Model	Threshold Method
0	128	0	0	BPSK	BPSK
1	128	0	0	BPSK	BPSK
2	128	4.1	0	BPSK	BPSK
3	128	33.3	0.02	BPSK	BPSK
4	128	107.8	11.8	BPSK	BPSK
5	128	236.4	63.7	8PSK	BPSK
6	128	383.2	182.0	8PSK	8PSK
7	128	496.6	363.6	8PSK	8PSK
8	128	555.7	551.6	8PSK	16QAM
9	128	575.2	685.1	16QAM	16QAM
10	128	576	749.6	16QAM	16QAM
11	128	576	767.7	16QAM	16QAM
12	128	576	768	16QAM	16QAM
13	128	576	768	16QAM	16QAM
14	128	576	768	16QAM	16QAM

with $R_c = 1/2$ for a difference of 4.1 bits, i.e., $T_{ij} - T_{kj} = 4.1$bits), and therefore this state has the lowest error tolerance level, and thus determines the robustness of the *simplified* model.

If $P_a = P_{-a}$, then the corresponding errors for **P** are $\{\epsilon_a, a = 0, 1, 2, 3\}$. To simplify calculation, we assume that the magnitude of ϵ_a is constant for $a = 0, 1, 2, 3$, say $|\epsilon_a| = \epsilon_0$, $a = 0, 1, 2, 3$. To find the maximum value for ϵ_a (denoted by ϵ_{max}) such that the optimal MCS is still selected, we solve the following equation for ϵ_a

$$(T_{ij} - T_{kj}) + \delta(T_{ij} - T_{kj}) = 0. \tag{11}$$

To find ϵ_{max}, we compute K_a's and arrange them in decreasing order. Then, noting that (10) is a linear function of $\{\epsilon_a, a = 0, 1, 2, 3\}$, we simply associate ϵ_{max} with the two smaller values, and $-\epsilon_{max}$ with the two larger values. This selection results in the most negative value for $\delta(T_{ij} - T_{kj}) = \sum_a \epsilon_a K_a$ while maintaining the condition that $\sum_a \epsilon_a = 0$. Then, we substitute the results in (11) and solve for ϵ_{max}.

We find that there are 6 cases to consider. The results are tabulated in Table III for all 6 cases. Note that '-' denotes the case where the particular error type can not result in $T_{ij} - T_{kj} = 0$, and consequently does not result in selection of a sub-optimal MCS; the last row in the table represents the worst case scenario in this state for the system as described earlier.

By assuming that all errors have the same magnitude, this approach finds the worst case scenario for the errors such that (10) is reduced to zero with the least value of magnitude of ϵ_a.

TABLE III

MAXIMUM ERRORS ALLOWED FOR ERROR TYPES IN STATE 8

Error Types $\{\epsilon_0, \epsilon_1, \epsilon_2, \epsilon_3\}$	ϵ_{max}
$\{-\epsilon_0, -\epsilon_0, \epsilon_0, \epsilon_0\}$	0.0072
$\{-\epsilon_0, \epsilon_0, \epsilon_0, -\epsilon_0\}$	-
$\{-\epsilon_0, \epsilon_0, -\epsilon_0, \epsilon_0\}$	-
$\{\epsilon_0, \epsilon_0, -\epsilon_0, -\epsilon_0\}$	-
$\{\epsilon_0, -\epsilon_0, \epsilon_0, -\epsilon_0\}$	-
$\{\epsilon_0, -\epsilon_0, -\epsilon_0, \epsilon_0\}$	0.0046

VI. CONCLUSION

In this paper, we evaluated the performance of Turbo Code based Adaptive Modulation and Coding in 3G wireless systems. We proposed a new method for selecting the appropriate Modulation and Coding Scheme according to the estimated channel condition where we use a first-order finite-state Markov model to represent the average channel SNR. We take a statistical decision making approach to address the potential problems caused by the sensitivity of Turbo Code to the errors in predicting the channel SNR. Numerical results are presented showing that our method substantially outperforms the conventional techniques that use a *threshold-based* decision making approach. We also propose a *simplified* model with fewer parameters which is suitable in systems where changes in the fading characteristics need to be accounted for in an adaptive manner. It is shown that the inherent approximation errors in the *simplified* model result in a negligible loss in the expected throughput.

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