A Game Theoretic Approach to Dynamic Energy Minimization in Wireless Transceivers

Ali Iranli, Hanif Fatemi and Massoud Pedram
Dept. of Electrical Engineering
University of Southern California
{iranli,fatemi,pedram}@usc.edu

Abstract: *Adaptive transceivers can significantly reduce the energy consumption of a mobile, battery-powered node by capturing real-time changes in the communication channel. This paper proposes a game-theoretic solution to the optimization of the energy consumption in wireless transceivers. This is accomplished by dynamically adapting the modulation level of the transmitter modulator and the error correction aptitude of the receiver decoder with respect to channel conditions subject to specified average bit-error-rate and throughput constraints. Experimental results demonstrate energy savings of up to 15%.*

1 Introduction

Extending the battery lifetime of mobile hosts in a mobile ad-hoc network (MANET) is a key design objective. Reducing the energy consumption in every mobile host is helpful in achieving this goal. However, the optimization scenario may be extended to consider tradeoffs between energy consumptions of two hosts that are participating in a data transaction, one serving as the sender of data, the other as the receiver.

A modern digital communication system, as depicted in Figure 1, consists of two transceivers. The base-band transceiver, which uses digital signal processing, encodes the input data bits so as to increase the data fidelity against unexpected changes in the channel characteristics. The pass-band transceiver, which uses analog signal processing, modulates digital data into analog symbols and guarantees a minimum received signal-to-noise-ratio (SNR). In order to design a low-energy communication system, the overall energy consumption of the transmitter and receiver should be considered. There are detailed studies of the trade-off between energy consumption and bit-error-rate (BER) in the communications field [1]. These studies can be grouped into two main categories. The first category of techniques, which focuses on the pass-band transceiver, exploits the fact that different modulation schemes result in different BER vs. SNR characteristics. The basic idea is to obtain different BERs by adaptively changing the modulation and/or equalization levels while keeping the received SNR at the receiver constant. In [2], it is shown that by dynamically reconfiguring the channel equalizer, an energy saving of up to 90% can be achieved. Reference [3] proposes an adaptive modulation scheme to decrease the BER while maintaining the transmit power level, and hence, saving energy. More recently, reference [4] has shown that by changing the modulation level of a pass-band transceiver, i.e., the channel rate, sizeable energy savings can be achieved.

The second category of techniques, which focuses on the base-band transceiver, studies the interaction between code performance and encoder/decoder design complexity. The main idea is to add a number of error controlling bits to the original data bits in order to guard them against channel changes. The key tradeoff is between the complexity of the encoding/decoding algorithms and the BER.

This research was supported in part by DARPA PAC/C program under contract DAAB07-02-C-P302 and by NSF under grant no. 9988441.

ICCAD'03, November 11-13, 2003, San Jose, California, USA.

In [5,6], the authors exploit the system characteristics to reduce energy consumption of a Reed-Solomon encryption processor. More recently, in [7], power consumption of a high memory-order punctured convolutional decoder has been reduced by using an adaptive algorithm based on the channel bandwidth and the received SNR, thereby, reducing the required energy for decoding a single bit of information.

All of the aforementioned techniques for energy reduction in communication systems (implicitly or explicitly) assume that the base-band and pass-band transceivers are independent. Consequently, energy-conserving optimizations are designed for the transmitter/receiver of one mobile host independent of what is happening to the receiver/transmitter of the other mobile host. In ad-hoc networks, the *RMS value of the total energy consumed* to support a fixed number of data transactions is a primary concern and local optimizations, which do not take into account the interactions between hosts, tend not to produce the maximum reduction in this value. In contrast, this paper introduces a new trade-off between a pass-band transmitter and a base-band receiver. Based on this trade-off, it is established that the overall energy consumption of a communication link (accounting for the energy consumptions of both the sending host and the receiving host) can effectively be minimized. The overall energy consumption in the network is subsequently minimized because the energy consumption of each communication link has been minimized. More precisely, the approach proposed in this paper combines adaptive modulation with adaptive Viterbi decoding in order to explore the new trade-offs between the energy consumptions of the pass-band transmitter and the base-band receiver in an Orthogonal-Frequency-Division-Multiplexing (OFDM) wireless system. In addition, a complete energy consumption model of a wireless node, i.e., transmitter and receiver, is proposed and various trade-offs between energy and Quality of Service (QoS) with respect to system parameters such as the transmit power level, channel condition, modulation scheme, and decoder complexity are studied.

This paper formulates the energy minimization problem in a MANET as a *hierarchical collaborative game* between the transmitter and the receiver of a communication system. In this game, players collaborate with one another to optimize the energy consumption of the system

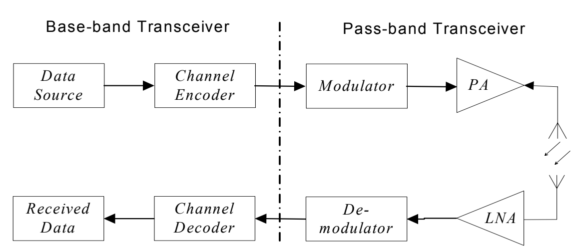


Figure 1. Communication system model

during a communication session. Player number one, i.e., the transmitter, minimizes the overall energy by setting the transmission power level and by adopting a set of modulation levels for different OFDM sub-carriers. Player number two, i.e., the receiver, optimizes the overall energy by choosing a set of decoding lengths for each sub-carrier to minimize the energy consumption of the decoder while maintaining a minimum required BER.

The remainder of this paper is organized as follows: Section II describes the energy model for a wireless communication system and provides the required background about modulation scaling and adaptive Viterbi decoding. The proposed model is then used in section III to define appropriate utility functions for the game theoretic framework and is setup for the collaborative game between the transmitter and receiver. Section IV describes the solution methods used in solving the game and sections V and VI present the experimental results and conclusions, respectively.

2 Background

In ad-hoc networks, a communication between two nodes starts with a route discovery session, which determines the actual links needed to establish a communication between a source and its destination. Then the process is followed by media access control, which grants the access to the wireless channel to the transmitter. Finally, the information packets are transferred hop by hop from the source to the destination. Therefore, not only the source and the destination hosts, but also all intermediate hosts on the established route consume energy to transfer the data. This paper aims at minimizing the overall energy consumption in the network by minimizing the energy consumption of each link (consisting of a pair of transmitter and receiver hosts) on the selected route. We consider a wireless system in which each mobile host has both transmission and reception capabilities. In such a system, the average energy consumption of a host is as follows:

$$E_{avg} = \alpha \cdot E_{Transmit} + (1-\alpha) \cdot E_{Receive} \quad (1)$$

where $E_{Transmit}$ and $E_{Receive}$ denote the power consumptions of the transmitter and the receiver, respectively. α denotes the fraction of transmitted data bits to the total data bits handled by node, e.g. $\alpha = 0.5$ represents the scenario where the node transmits and receives the same amount of data.

2.1 Transmitter Energy Model

The total power consumption of transmitter can be written as:

$$P_{Transmit} = P_{Enc} + P_{Mod} + P_{Amp} \quad (2)$$

where P_{Enc}, P_{Mod}, and P_{Amp} denote power consumptions of the corresponding blocks in the transmitter. The dominant term among all these terms is the power consumption of the amplifier, P_{Amp}. The other terms are smaller in magnitude and depend linearly on the symbol rate with an additive constant term. Hence, for our optimization purposes, the total power consumption of transmitter may be approximated as:

$$P_{Transmit} \cong P_{Tx} \cdot R_s + P_{const} + P_{Amp} \quad (3)$$

where P_{Tx} and P_{const} are the symbol-rate-dependent and constant power consumption components of the base-band transmitter, where R_s denotes the symbol rate. To characterize the BER in terms of the power consumption of the transmitter, the relationship between the received SNR and the BER of the pass-band transceiver, i.e., the modulating/demodulating pair, can be used. For example, consider a QAM modulation scheme where the BER is related to the received SNR by the following equation [1]:

$$BER = 1 - (1 - P_{\sqrt{M}})$$
$$P_{\sqrt{M}} = 2\left(1 - \frac{1}{\sqrt{M}}\right).Q\left(\sqrt{3\frac{SNR_{received}}{M-1}}\right) \quad (4)$$

where M is the number of *constellation points* in the QAM modulation, typically $M = 2^b$ and b is the number of information bits represented by each constellation point. $SNR_{received}$ is the received signal-to-noise-ratio at the receiver. Let N_0, β, and R_s denote the noise spectral density, the spectral shaping factor, and the symbol rate, respectively. The received *SNR* is related to the transmit power level P_{Amp}, noise in the channel P_{Noise}, and the path loss parameter, λ, by [1]:

$$SNR_{received} = \frac{P_{Amp}}{P_{Noise}} \cdot \lambda = \frac{P_{Amp}}{N_0 \cdot \beta \cdot R_s} \cdot \lambda \quad (5)$$

For a given BER and modulation scheme, i.e., for fixed b, one can calculate the required SNR, from equation (4), and then use equation (5) to find the minimum required transmit power level. To calculate the required energy for transmitting a single symbol, the overall power consumption of the transmitter given by equation (3), should be divided by number of symbols per second or R_s.

2.2 Receiver Energy Model

Power consumption of the receiver is due to power consumptions of the low noise amplifier, the demodulating block, and the channel decoding block. The total power consumption of the receiver can thus be written as:

$$P_{Receive} = P_{LNA} + P_{Demod} + P_{Dec} \quad (6)$$

where P_{LNA}, P_{Demod}, and P_{Dec} denote the power consumptions of the corresponding blocks in the receiver. Considering that all other blocks except the channel decoder are fixed and do not respond to changes in channel conditions, for optimization purposes, the receiver power consumption may be approximated as:

$$P_{Receive} \cong P_{Rx} \cdot R_s + P_{const} + P_{Dec} \quad (7)$$

where P_{Rx} and P_{const} are the symbol-rate-dependent and constant components of power consumption of the pass-band receiver.

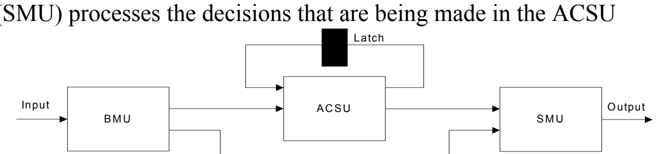
Typically, a channel decoder is a multi-stage implementation of a recursive decoding function. Therefore, the accuracy of decoding increases as the number of decoding stages (iterations) increases. On the other hand, increasing the number of stages boosts the power consumption of the decoder. In this work, a Viterbi decoder is studied as the channel decoder.

In Adaptive Viterbi Algorithms (AVA), developed in [7-9], the decoding performance is increased by reducing the number of operations required to decode a single bit. This is achieved by reducing *truncation length* (*TL*) or by reducing the number of *survivor paths*, i.e., those paths that are kept in order to find the optimum path. There are two main variations of the AVA. In the first variation, which is called the *T-Algorithm* [9], a fixed Threshold, *T*, is chosen and then those paths that have path metrics equal to or less than *T* are included in the survivor path memory. In the second variation, called the *M-Algorithm* [10], a fixed number of paths, *M*, are kept and all other paths are discarded. These paths are selected by choosing the first *M* paths with the minimum path metric values.

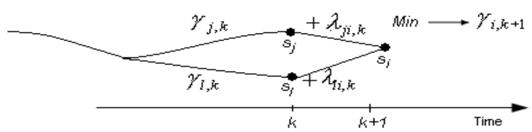
Consider an adaptive Viterbi decoder with the functional block diagram depicted in Figure 2a. The decoder can be divided into three basic units. The input data (that is, the noisy observation of the encoded information bits) is used in the Branch Metric Unit (BMU) to calculate the set of branch metrics $\lambda_{ij,k}$. These are then fed to the Add-Compare-Select Unit (ACSU) to update the path metric cost according to the following recursive equation:

$$\gamma_{i,k+1} = \min\left(\gamma_{j,k} + \lambda_{ji,k}, \gamma_{l,k} + \lambda_{li,k}\right) \qquad (8)$$

where $\gamma_{i,k}$ is the path metric cost for state s_i in time step k, and $\lambda_{ji,k}$ is the branch metric cost between states s_i and s_j from time instances k and $k+1$, respectively (cf. Figure 2b). The Survivor Memory Unit (SMU) processes the decisions that are being made in the ACSU



a. Block diagram of Viterbi decoder



b. Finding the optimum path

Figure 2. Adaptive Viterbi decoder

in order to carry out the ACS-recursion and outputs the estimated path, with a latency of at least *TL*.

Power consumption for an adaptive Viterbi decoder can be macro-modeled by adding up the power consumption of each block times the number of paths that block is being used. This would result in following proposed power macro-model:

$$P_{Dec} = \left[P_{BMU} + 2^{K}.\left(2P_{adder} + P_{comp} + TL.P_{SMU}\right)\right] \qquad (9)$$

where P_{BMU}, P_{Adder}, P_{Comp}, P_{SMU} are the per-operation power consumptions of the BMU, the adder, the comparator, and the SMU, respectively, and K is the memory depth of corresponding convolutional encoder.

2.3 Energy optimization problem

As shown in the previous sections, energy consumption of a communication link is a strong function of the characteristics of the wireless channel. Potentially, one can reduce the energy required to transfer a single bit of information by optimizing the transceiver parameters to match the channel characteristics. The key problems lie in having to first estimate the channel characteristics and second find the appropriate set of transceiver parameters. In the following, we explain how these two problems are addressed by our proposed approach.

We assume that in each time slot the receiver provides an estimate of the channel characteristics and information about its remaining energy level to the transmitter. Using this data and information about the remaining energy of the transmitter itself, the transmitter must solve a mathematical optimization problem that would yield the energy optimal set of modulation levels and the transmit power level.[1] Note that this mathematical program has as the objective function the energy consumption per bit in the transmitter and the receiver of the link and as constraints the minimum throughput and the maximum bit-error-rate. The transmitter then uses the results of this optimization for the next data transmission. These parameters are kept unchanged until the channel conditions change or the remaining energy levels of the two nodes drop by more than a fixed percentage at which time the transmitter will have to deploy a different policy. Meanwhile, given the set of transmitter parameters, while receiving information, the receiver must minimize its own energy consumption. It does so by solving a mathematical programming problem similar to that solved by the transmitter. This time, however, the variable of optimization is the receiver implementation parameters.

From the above discussion, it should be evident that either the receiver or the transmitter alone cannot do this optimization optimally. More precisely, when the transmitter attempts to determine the optimal transmit parameter values at time t, it relies on an estimate of the receiver behavior and channel conditions at time $t\text{-}\Delta t$. In contrast, when the receiver tries to determine the optimal receive parameter values at time $t+\Delta t$, it relies on known transmit parameter values and channel conditions at time $t+\Delta t$. So, although it is possible for the transmitter and/or the receiver to set up a global problem, which determines the parameters of the receiver and the transmitter at the same time, the solution can be quite erroneous, especially when the channel conditions change rapidly. That is why we have set up the problem as a *Stackleberg game* as described next.

3 A Game Theoretic Formulation

3.1 Background

In his monograph about the market economy [11], H. V. Stackelberg used a hierarchical model to describe real market situations. His model captured a scenario in which different decision makers attempt to make the best decisions in a market with respect to their own, generally different, utility functions. Generally speaking, these decision makers cannot determine their course of action independently of each other; rather, they are forced to act according to a certain hierarchy. Consider a simple case of such a problem where there are only two active decision makers. The hierarchy classifies these two decision makers into a leader, who acts independently of the market, and a follower, who has to act in a dependent manner. The leader is able to dictate the selling prices or to overstock the market with his products, but in making his decisions, he has to anticipate the possible reactions of the follower since his profit strongly depends not only on his own actions but also on the response of the follower. On the other hand, the choice of the leader influences the set of possible decisions as well as the objectives of the follower who in turn must react to the selections of the leader.

The aforementioned problem can mathematically be formulated as follows: Let X and Y denote the set of admissible strategies x and y of the follower and of the leader, respectively. Assume that the values of the choices are measured by the means of the functions $f_L(x,y)$ and $f_F(x,y)$, denoting the utility functions of the leader and follower, respectively. Then, with the knowledge of the selection y of the leader, the follower can select his best strategy $x(y)$ so that his utility function is minimized on X:

$$x(y) \in \Psi_L(y) \text{ where } \Psi_L(y) = \underset{x}{Argmin}\left\{ f_F(x,y) \middle| x \in X \right\} \qquad (10)$$

Being aware of this selection, the leader solves a Stackelberg game [11] for computing his best selection:

$$\underset{y}{Argmin}\left\{ f_L(x,y) \middle| y \in Y, x \in \Psi_L(y) \right\} \qquad (11)$$

Notice that solutions to the Stackelberg game are different from the Nash equilibrium points due to the special hierarchy that is imposed on the players. In Nash equilibrium solution, all players are at the same level of hierarchy and make decisions simultaneously, but in a Stackelberg game, the decisions are made one after the other following certain rules. In general, in an N-player Stackelberg game

[1] Notice that in reality neither the transmitter nor the receiver actually solves a mathematical program at runtime. Instead, each has a policy table in which corresponding to various channel conditions and remaining energy levels, the parameters of a particular policy are stored. So all that the transmitter or the receiver will have to do is to do a low cost table lookup to read the parameter values and use them.

all players at the same level achieve the Nash's equilibrium point, but this is not true for players at different levels of hierarchy.

3.2 Application to Modulation and Coding

In our context, the leader and the follower become the transmitter and the receiver, respectively. Strategy *x* for the receiver is the adoption of a specific vector of truncation lengths (*TL*'s) for sub-carriers, and $X = \{(TL_1, TL_2, \cdots, TL_n) | \forall i : TL_i \in TLS\}$ where *n* is the number of sub-carriers in the OFDM signal and *TLS* denotes the set of all (feasible) *TL*'s for the adaptive Viterbi decoder. Strategy *y* for the transmitter is a choice of specific overall transmission power level and a set of modulation levels for the different sub-carriers from $Y = \{(P_{Tx}, b_1, b_2, \cdots, b_n) | \forall i : b_i \in MLS, P_{Tx} \in PLS\}$ where *MLS* and *PLS* denotes the sets of (feasible) modulation levels for each sub-carrier and available power levels for transmission. These sets are known from the chipset specification or the standard protocol supported by the chipset. Note that this formulation can easily be extended to take into account different transmit power levels for each sub-carrier. This case is not explored here because this would require multiple output amplifiers (one per sub-carrier) in order to support independently-controlled power levels per sub-carrier. This is quite expensive from implementation point of view.

The utility function for the receiver (follower), $f_F(x, y)$, is the amount of energy required to achieve a specified BER given the received SNR. To calculate this energy, first the required truncation length for each sub-carrier is determined by using a lookup table, and then by plugging these *TL* values into equations (7) and (9) to obtain the overall energy consumption of the receiver. Since the OFDM symbols are being transmitted at a constant rate, we can factor the power coefficients and drop the constant values of equation resulting in the following optimization problem in the receiver:

$$\min_{\hat{X}} \left\{ \left\langle I, \hat{X} \right\rangle : A\hat{X} + B\hat{Y} \le R\hat{E}Q_{Rx}, \hat{X} \in TLS^n \right\} \quad (12)$$

where *I* is the identity vector and $\langle a, b \rangle$ denotes the inner product of vectors *a* and *b*. $\hat{X}$ and $\hat{Y}$ denote strategies of the receiver and the transmitter, respectively. *A* and *B* are the coefficient matrices that account for the channel characteristics and power consumption of the basic building blocks of the receiver. $R\hat{E}Q_{Rx}$ is a vector representing the upper bound on overall energy consumption and required BER as shown in (13).

$$\hat{X} \triangleq \begin{bmatrix} TL_1 \\ TL_2 \\ \vdots \\ TL_{n-1} \\ TL_n \end{bmatrix} \quad \hat{Y} \triangleq \begin{bmatrix} P_{Tx}/R_S \\ b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix} \quad R\hat{E}Q_{Rx} \triangleq \begin{bmatrix} E\_max \\ BER_1 \\ BER_2 \\ \vdots \\ BER_n \end{bmatrix}$$

$$A \triangleq \overbrace{\begin{pmatrix} 2^k \cdot P_{SMU}/R_S & 2^k \cdot P_{SMU}/R_S & \cdots & 2^k \cdot P_{SMU}/R_S \\ \alpha_{BER_1} & 0 & \cdots & 0 \\ 0 & \alpha_{BER_2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \alpha_{BER_n} \end{pmatrix}}^{(n+1)\times n} \quad B \triangleq \overbrace{\begin{pmatrix} 1 & 0 & 0 & \cdots & 0 \\ 0 & \beta_{BER_1} & 0 & \cdots & 0 \\ 0 & 0 & \beta_{BER_2} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \beta_{BER_n} \end{pmatrix}}^{(n+1)\times(n+1)} \quad (13)$$

where α_{BER_i} and β_{BER_i} are empirical coefficients for linear estimation of BER for i^{th} sub-carrier in terms of the modulation level and the truncation length of the decoder. The optimization problem at the transmitter (leader) can be viewed as a minimization of the overall energy consumption of the system, given the estimated channel transfer function for the next time slot. This can mathematically be formulated as:

$$\min_{\hat{Y}} \left\{ \left\langle I, \hat{X} \right\rangle + \left\langle U, \hat{Y} \right\rangle : D\hat{Y} \ge R\hat{E}Q_{Tx}, \hat{Y} \in PLS \times MLS^n, \hat{X} \in \Psi_L(\hat{Y}) \right\} \quad (14)$$

where *U* is a singleton vector as shown in (15), and *D* is the coefficient matrix for linear estimation of the throughput and BER in terms of the SNR and the modulation level. $R\hat{E}Q_{Tx}$ is a vector representing the minimum requirements for the throughput and BER.

$$U \triangleq \begin{bmatrix} 1 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \quad R\hat{E}Q_{Tx} \triangleq \begin{bmatrix} Thru\_put \\ BER_1 \\ BER_2 \\ \vdots \\ BER_n \end{bmatrix} \quad D \triangleq \overbrace{\begin{pmatrix} 0 & 1 & 1 & \cdots & 1 \\ ch_1 & \delta_{BER_1} & 0 & \cdots & 0 \\ ch_2 & 0 & \delta_{BER_2} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ ch_n & 0 & 0 & \cdots & \delta_{BER_n} \end{pmatrix}}^{(n+1)\times(n+1)} \quad (15)$$

where ch_i and δ_{BER_i} are the estimated channel transfer function and the BER estimation coefficient for sub-carrier *i*.

4 Solution to Minimum Energy Stackelberg Game

The Stackelberg game can be solved using *multi-level optimization* methods [13]. First we note that, with the assumption of collaboration among players, the leader is able to influence the follower to select in each case the solution out of $\psi_L(y)$ which is the best for the leader. This results in the so-called *optimistic* or *weak bi-level programming problem*:

$$\min_{\hat{X}, \hat{Y}} \left\{ \left\langle I, \hat{X} \right\rangle + \left\langle C, \hat{Y} \right\rangle : D\hat{Y} \ge R\hat{E}Q_{Tx}, \hat{Y} \in PLS \times MLS^n, \hat{X} \in \Psi_L(\hat{Y}) \right\} \quad (16)$$

in which the objective function is minimized with respect to the upper and lower level variables. The optimal solution of problem (16) is known as the *optimistic optimal solution* to the Stackelberg game [14].

Definition 4.1: A point-to-set mapping $\Gamma : \mathbb{R}^p \to 2^{\mathbb{R}^q}$ is called *polyhedral* if its graph

$$G(\Gamma) \triangleq \left\{ (x, y) \in \mathbb{R}^q \times \mathbb{R}^p \,\middle|\, x \in \psi_L(y) \right\}$$

is equal to the union of a finite number of *convex polyhedral sets*. Here a *convex polyhedral set* is the intersection of a finite number of half-spaces [12].

Theorem 4.1: The point-to-set mapping $\psi_L(\cdot)$ of a Stackelberg game (14) is polyhedral.
Proof: Refer to [13].

Theorem 4.2: If there exists at least one solution for the lower level problem (12) for each value of $\hat{Y}$, then there exists an optimal solution for the corresponding optimistic Stackelberg game (16) which is a vertex of the set

$$\left\{ (\hat{X}, \hat{Y}) \,\middle|\, A\hat{X} + B\hat{Y} < R\hat{E}Q_{Rx}, D\hat{Y} \ge R\hat{E}Q_{Tx}, \hat{X}, \hat{Y} \ge 0 \right\} \quad (17)$$

Proof: Refer to [14].

Using the above-mentioned theorems, the space to search for the solutions of the problem at hand shrinks to the vertices of the set given in (17). Based on these theoretical results, we propose an enumerative algorithm, *Solve_MESG* (cf. Figure 3) to solve the *Minimum Energy Stackelberg Game* (MESG).

The algorithm starts with initializing the *minimum_energy* value to infinity and then for each subset of indices *I* (line 2) finds the corresponding vertex of the polyhedral and its energy value using a linear equation solver function, *solve_equation,* in line 3. If the newly found vertex results in a lower energy value, the current solution is updated (lines 4&5). The algorithm iterates till it covers all of the vertices. Notice that the *solve_equation* function solves a system of linear equations with linear constraints as given below:

$$
\begin{aligned}
&\left(A\hat{X} + B\hat{Y} - R\hat{E}Q_{Rx} = 0\right)_i \ \forall i \in I \\
&\left(A\hat{X} + B\hat{Y} - R\hat{E}Q_{Rx} \leq 0\right)_j \ \forall j \notin I \qquad (18) \\
&D\hat{Y} \geq R\hat{E}Q_{Tx}
\end{aligned}
$$

where operator $(V)_i$ provides the i^{th} element of the vector V. If a solution exists for the linear equation system, the function would then return the value of the energy consumption for the solution point using (16); otherwise, it returns infinity.

5 Experimental Results

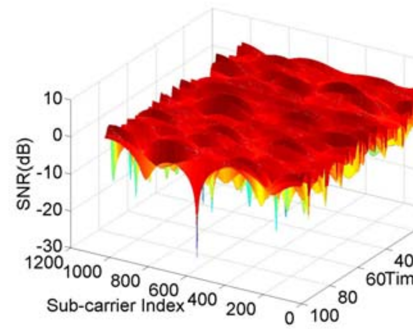
To show the effectiveness of the proposed adaptive modulation and decoding scheme in practical scenarios, the *IEEE 802.11a* standard [15] is studied. This standard uses an OFDM modulation scheme and also benefits from the FEC codes based on convolutional codes. The standard has 64 sub-carriers, where 48 of them are data sub-carriers, 4 of them are pilot sub-carriers, and the rest are used for spectral shaping purposes. In order to simulate the system, Simulink 5.0 environment from *Matlab 6.5 Release 13* is used.

To model a multi-path fading channel, a parallel combination of Rayleigh and Rician fading propagation channels is used [16]. The maximum Doppler shift and the spreading factor of the Rician fading channel are set to 40*Hz* and 1, respectively. In order to take into account the effect of multi-path fading, three different paths with delays of 2*us,* 3*us,* and 5*us* and gains of –3, 1, and 2 are considered in the Rayleigh propagation channel. A typical characteristic of this channel is shown in Figure 4a. As shown in section II, an estimate of the channel characteristics is required to utilize the new adaptive modulation and decoding technique. A coarse, but useful, estimate of channel can be calculated based on the magnitude of received pilot signals. The channel is then approximated by a flat channel with the same magnitude over the frequency band of 12 sub-carriers adjacent to each pilot sub-carrier (see Figure 4b). This channel estimate is then used to dynamically change the modulation level and decoding accuracy of the transmitter and receiver, respectively.

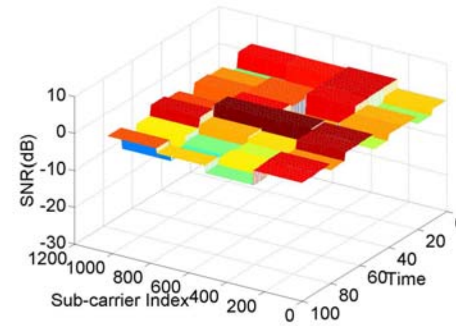
In the first set of experiments, a fixed decoder is used and the effect of adaptive modulation based on the estimated channel characteristic is reported. Figure 5 shows the average BER for different SNR values for adaptive and fixed modulation schemes. To further analyze the proposed multi-band adaptive modulation scheme, another scenario is considered in which a single modulation level is adaptively chosen for all sub-carriers based on the average behavior of the channel [4]. From Figure 5, one can conclude that the multi-band adaptive modulation can achieve up to two times reduction in BER compared to the simple adaptive scheme of [4]. Note that by increasing SNR, both multi-band and simple adaptive schemes increase the number of constellation points in each sub carrier, hence, for large SNR values, their BER vs. SNR curves converge to that of a fixed modulation scheme.

```
Solve_MESG( A, B, D, REQ_Tx, REQ_Rx, K)
Begin        // n is the number of sub-carriers
1.    minimum_energy=infinity;
2.    for all subsets I with maximum cardinality K of the
index set {1, 2,…, n+1}
      begin
3.        energy=solve_equation(A, B, D, I, REQ_Tx REQ_Rx);
4.        if energy<minimum_energy then
5.            minimum_energy=energy;
      end
end
```

Figure 3. Algorithm for solving the MSEG problem



(a) *Actual channel characteristics*



(b) *Channel estimation using pilot values*

Figure 4. Channel estimation

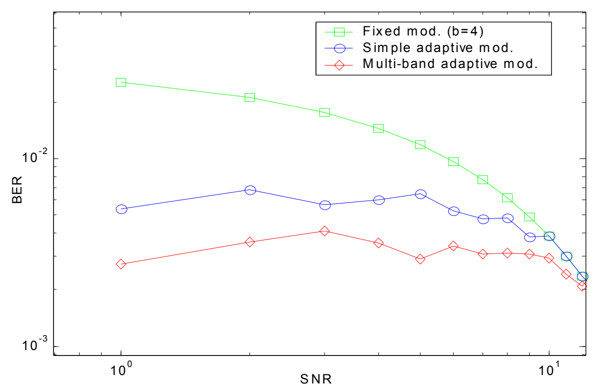
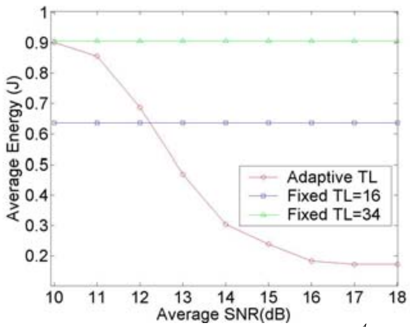


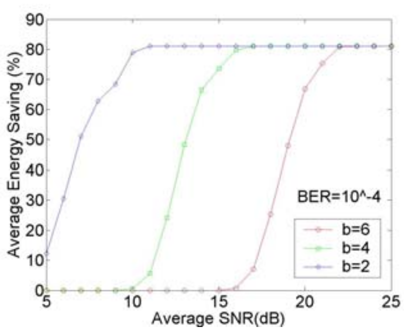
Figure 5. Average BER as a function of SNR for adaptive and fixed modulations

In the second set of experiments, a fixed modulation level is chosen and the effect of variable decoding length on average energy consumption is studied. Figure 6a shows average energy consumption of the receiver in a case where the targeted BER is 10^{-4} and the 16QAM modulation is used for all sub-carriers. Adaptive decoding scheme will consume more energy in low SNR values comparing to fixed *TL*=16 decoder to achieve the required BER. The average energy saving percentage for different modulation levels and number of constellation points is shown in Figure 6b for BER=10^{-4}.

The third set of experiments studies the overall energy consumption of the wireless system. In these experiments two different configurations of a wireless system is used. The *base-line system* is a system without any adaptive parameter except for the transmit power. Transmit power in base-line system is adaptively changed based on the average BER required on the receiver side. The *optimized system* refers to the adaptive transceiver proposed here. Figure 7 shows the normalized energy consumption of these two systems for different values of parameter α in equation (1). These results show an energy saving of up to 15% for the optimized system. Notice that as the average BER is decreased, i.e., requirements become harder to meet, the energy savings increase, this is due to the fact that a decrease in required BER causes the transmit power to increase. Thus the number of feasible choices for the modulation level and the truncation length accordingly would increase, providing the Stackelberg game solver with more possible strategies to choose from and hence enhancing the solution.



(a) *Average Energy vs. SNR (BER=10^{-4} & b=4)*



(b) *Average Energy saving (BER=10^{-4})*

Figure 6. Energy saving in the receiver for adaptive coding

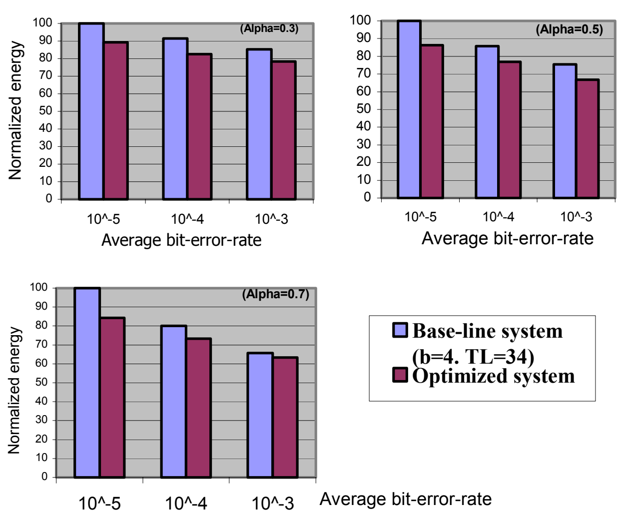


Figure 7. Normalized energy consumptions

6 Conclusions

A concurrent adaptive modulation and coding technique was proposed to minimize the RMS value of the total energy consumed to perform a fixed number of data transactions in a MANET. A new trade-off between energy consumption of the receiving party and that of the transmitting party was explored. A new metric based on energy, throughput and BER was introduced and used to dynamically set the system parameters in response to variations in channel characteristics. Experimental results demonstrated significant energy savings.

References

1. J. Proakis, *Digital Communications*, McGraw-Hill, 3rd Edition, 1995.
2. M. Goel and N.R. Shanbhag, "Low-power equalizers for 51.84 Mb/s very high-speed digital subscriber loop (VDSL) modems," in *Proc. of IEEE VLSI Signal Processing Workshop*, (Boston, MA), Oct. 1998.
3. T. Ue, S. Sampei, N. Morinaga, and K. Hamaguchi, "Symbol rate and modulation level-controlled adaptive modulation/TDMA/TDD system for high-bit-rate wireless data transmission," *IEEE Trans. on Vehicular Technology*, Vol. 47, No. 4, pp. 1134-1147, Nov. 1998.
4. C. Schurgers, V. Raghunathan, and M.B. Srivastava, "Modulation scaling for real-time energy aware packet scheduling," in Proc. of IEEE Global Telecommunication, Vol. 6, pp. 3653 –3657, 2001.
5. J. Goodman, A. Chandrakasan, and A. Dancy, "Design and implementation of a scalable encryption processor with embedded variable DC/DC converter," in *Proc. of Design Automation Conf.*, pp.855-860, Jun. 1999.
6. M. Goel and N. Shanbhag, "Low-power channel coding via dynamic reconfiguration," in *Proc. of Int'l Conf. on Acoustics Speech and Signal Processing*, pp. 1893-1896, Mar. 1999.
7. R. Henning and C. Chakrabarti, "Low-power approach to decoding convolutional codes with adaptive viterbi algorithm Approximations," in *Proc. of Int'l Symp. on Low Power Electronics and Design*, pp. 68 –71, Aug. 2002.
8. F. Chan and D. Haccoun, "Adaptive Viterbi Decoding of Convolutional Codes over Memory less Channels," *IEEE Trans. on Comm*., Vol. 45, No. 11, pp. 1389-1400, Nov. 1997.
9. S. Swaminathan, R. Tessier, D Geockel, and W. Burleson, "A dynamically Reconfigurable Adaptive Viterbi Decoder," in Proc. of the FPGA Conf., Monterey, California, Feb. 2002.
10. C. F. Lin and J. B. Anderson, "M-Algorithm Decoding of channel convolutional Codes," in *Proc. of Princeton Conf. of Information Science and System*, pp 362-366, Princeton, NJ, Mar. 1986.
11. H.v. Stackelberg, "Marktfrom und Gleichgewicht," Springer-Verlag, Berlin 1934. engl. Transl. *The theory of the Market Economy*, Oxford University Press, 1952.
12. R.T.Rockafeller, "Convex Analysis," Princeton University Press, Princeton, 1970.
13. Stephan Dempe, *Foundations of Bilevel Programming*, Kluwer Academic Publishers, Boston, 2002.
14. J.F.Brad, "Optimality conditions for bi-level programming," Naval Research Logistics Quarterly, Vol. 31, pp.13-26, 1984.
15. 802.11a/b Standard Spec. IEEE, http://ieeexplore.ieee.org/xpl/standards.jsp.
16. Wireless propagation bibliography, http://w3.antd.nist.gov/wctg/manet/wirelesspropagation_bibliog.html
17. R.A. Freking, K.Parhi, "Theoretical Estimation of Power consumption in Binary adders," *Proc. of the IEEE Int'l Symposium on Circuits and Systems*, Vol. 2, 31 May 1998.