Power Optimization of Wireless Systems Utilizing Space-Time Block Coding and Successively Refinable Source Coding

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***Abstract*— In this paper, power optimization of wireless systems utilizing multiple transmit antennas and successively refinable source coding is considered. We present a solution to a formulation of an optimization problem aimed at minimizing total power consumption of such wireless systems subject to a given level of QoS and an overall available bit rate. Our formulation takes into consideration the power consumption related to source coding, channel coding, and layered transmission of multiple transmit antennas. In our study, we consider a Gauss-Markov source model, a Rayleigh fading channel along with the Gilbert-Elliott loss model, and a space-time transmission block code.**

***Index Terms*— Wireless Layered Systems, Power Optimization, Source Coding, Channel Coding, Multiple Transmit Antenna Systems, Space-Time Block Codes, Gilbert-Elliott Loss Model, QoS, Rate, Distortion.**

I. Introduction

THE emergence of new wireless standards is expected to expedite more frequent use of mobile devices. More frequent and longer use of mobile devices is naturally equivalent to higher power consumption. Consequently in order to extend the lifetime of the limited power resources of such devices, their power consumption has to be kept to a minimum level. On the contrary, providing the desired level of Quality of Service (QoS) in presence of the fading effects of multipath wireless channels necessitates higher consumption of power in mobile devices. Successively refinable coding also known as layered coding has proven as an efficient technique in transmitting content to a set of heterogeneous receivers. The technique relies on the ability of many compression schemes to divide their output bit stream into layers; a base layer and one or more enhancement layers. The base layer can be independently decoded providing a basic level of QoS. The enhancement layers can only be decoded together with the base layer to provide improvements to QoS.

In what follows we briefly review some of the specific literature articles in the context of transmitting multimedia content across a wireless backbone. In an early work Lan et al. [11] solved an energy optimization problem subject to the quality of service when transmitting images across the wireless backbone. Goel et al. [7] solved another image transmission energy optimization problem subject to distortion and rate constraints. While they appropriately considered hardware specific impacts in their work, their analysis lacked a consideration of channel coding and transmission system. Havinga [8] considered energy efficiency in channel coding techniques for wireless systems without considering the energy of source coding and transmission. Considering transmission, source, and channel coding components, Appadwedula et al. [2] formulated and solved an energy optimization problem subject to statistical distortion and rate constraints for transmitting images over wireless channels. Ji et al. [10] proposed a joint source-channel coding technique with unequal error protection to solve a power optimization problem subject to distortion and rate constraints for transmitting video across the wireless backbone. Lu et al. [12] solved a similar power optimization problem subject to an end-to-end distortion relying on H.263 source coding scheme and Reed-Solomon channel coding in conjunction with the Gilbert loss model. In [9], we formulated and analytically solved the power optimization problem of memoryless wireless media systems with space-time block codes subject to an end-to-end distortion and rate constraints. In our study, we relied on H.263 source coding scheme and Reed-Solomon channel coding standard in conjunction with the Bernoulli loss model. In [15], we extended our work to the channels with memory by considering the Gilbert-Elliott loss model. We note that the study of [15] did not consider any layered source coding.

The theme representing the goal of this paper is to solve the power optimization problem when layered source coding is utilized. The study addresses the tradeoff between the power consumption and the QoS in successively refinable wireless systems utilizing multiple transmit antenna systems. This is a progression of our earlier work moving from single layer coding systems to multi layer coding systems.

An outline of the paper follows. In Section II, we provide an analysis of the underlying wireless system consisting of transmitting, channel, and receiving sides. In Section III, we formulate and analytically solve our power optimization problem subject to distortion and rate constraints. In Section IV, we numerically validate our analytical results. Finally, Section V includes a discussion of concluding remarks and future work.

II. An Analysis of System Components

In this section, we provide an analysis of the system components. We assume that we are transmitting the signal in K layers. The number of layers K is a design parameter addressing the tradeoff between the source coding overhead and the QoS granularity. We start by providing an analysis of wireless fading channel and the transmission system. We then continue by focusing on the analysis of loss and our proposed channel coding technique. Finally, we complete our discussion by describing a layered transmission scheme for a Gauss-Markov source.

A. Fading Channel and Transmission Analysis

For the analysis of the wireless fading channel, we rely on the so-called Rayleigh model with a fading factor α. We recall that for a multipath slow fading Rayleigh wireless channel, the average received signal to noise ratio $\overline{SNR}_k$ of layer k at a receiver demodulator is expressed as

$$\overline{SNR}_k = \mathcal{E}[|\alpha|^2]\,\frac{E_{sym,k}}{N_0} \tag{1}$$

where $\mathcal{E}$ denotes the expectation operator, $|\alpha|$ has a Rayleigh distribution, $E_{sym,k}$ is the transmission energy at layer k per symbol interval, and N_0 is the one-sided spectral density of the white Gaussian noise. Utilizing the results of Simon et al. [13] and the proper choice of normalization factors, the symbol error rate of a single transmit, single receive antenna system at layer k for a slow fading Rayleigh channel utilizing BPSK modulation scheme is expressed as

$$e_{sym,k} = \tfrac{1}{2}\,\{1 - \sqrt{\tfrac{\overline{SNR}_k}{1+\overline{SNR}_k}}\} \tag{2}$$

Similarly, the result for the QPSK modulation scheme is expressed as

$$e_{sym,k} = \tfrac{3}{4}\,\{1 - \tfrac{4}{3\pi}\sqrt{\tfrac{\overline{SNR}_k}{2+\overline{SNR}_k}}\,[\tfrac{\pi}{2} + \arctan\sqrt{\tfrac{\overline{SNR}_k}{2+\overline{SNR}_k}}]\} \tag{3}$$

Further, the closed forms for the symbol error rate of a two transmit, single receive antenna system at layer k in a slow fading Rayleigh channel utilizing the space-time block codes of [1] and [14] can also be carried out from [13]. The details of calculation are reported in [15]. The symbol error rate of layer k for a double transmit single receive antenna system utilizing BPSK modulation scheme is expressed as

$$e_{sym,k} = \tfrac{1}{2}\,\{1 - \sqrt{\tfrac{\overline{SNR}_k}{2+\overline{SNR}_k}}\,[1 + \tfrac{1}{2+\overline{SNR}_k}]\} \tag{4}$$

Similarly for a double transmit single receive antenna system, the result for the QPSK modulation scheme is expressed as

$$\begin{aligned} e_{sym,k} &= \tfrac{3}{4} - \tfrac{\zeta}{\pi}\,\{(\tfrac{\pi}{2} + \arctan\zeta)(1 + \tfrac{2}{4+\overline{SNR}_k}) \\ &\quad + \sin(2\arctan\zeta)(\tfrac{1}{4+\overline{SNR}_k})\} \end{aligned} \tag{5}$$

where $\zeta = [(\overline{SNR}_k)/(4+\overline{SNR}_k)]^{1/2}$.

B. Loss and Channel Coding Analysis

Having specified the symbol error rate based on the channel characteristics, we propose utilizing a per layer Reed-Solomon channel coder $RS(n, m_k)$ that converts m_k information symbols in layer k into an n-symbol block as the result of appending $(n-m_k)$ parity symbols. Assuming $R_{s,k}$ and $R_{c,k}$ respectively denote source and channel coding bit rates at layer k, we note that utilizing such a channel coding scheme introduces a channel code rate of $r_k = \frac{m_k}{n} = \frac{R_{s,k}}{R_{s,k}+R_{c,k}}$. The scheme also allows for correcting $t_c = \lfloor\frac{n-m_k}{2}\rfloor$ symbol errors. In order to calculate the error rate of a block utilizing an $RS(n, m_k)$ coder, we consider the two-state Gilbert-Elliott error model of [6] and [4] representing a channel with memory. We note that simpler representations of error models namely the single-state Bernoulli and the two-state Gilbert [6] models can be viewed as special cases of the more general Gilbert-Elliott model. Although investigating the simpler cases are attractive from the stand point of providing analytical solutions, due to lack of space we only focus on the general model in this paper. The interested reader is referred to [15] for the details of other models.

As pointed out in many research articles, a multipath fading wireless channel typically undergoes burst loss representing temporally correlated loss. The two-state Gilbert-Elliott loss model provides an elegant mathematical model to capture the loss behavior of ever-changing channel conditions. In the Gilbert-Elliott model, symbol loss is described by a two-state Markov chain as described in Fig. 1. The first state G known as the GOOD state represents the loss of a symbol with probability e_G while the other state B known as the BAD state represents the loss of a symbol with probability e_B where $e_B >> e_G$. The GOOD state also introduces a probability $P_G = \gamma$ of staying in the GOOD state and a probability $1 - P_G$ of transitioning to the BAD state while the BAD state introduces a probability $P_B = \beta$ of staying in the BAD state and a probability $1 - P_B$ of transitioning to the GOOD state. The parameters γ and β can be typically measured from the observed loss rate and burst length. We recall that in our layered model, the probability of loss in the GOOD sate $e_{sym,G,k}$ is a function of the average received signal to noise ratio of the GOOD state. Similarly, the probability of loss in the BAD sate $e_{sym,B,k}$ is a function of the average received signal to noise ratio of the BAD state. For the Gilbert-Elliott loss model, the probability of receiving exactly m_k symbols from n transmitted symbols in layer k is described by

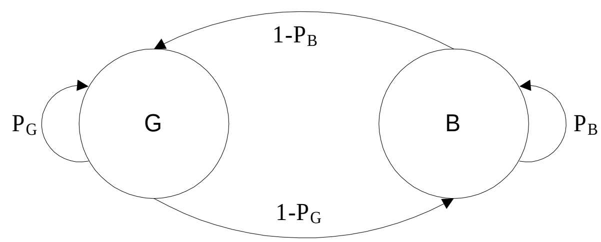

Fig. 1. The two-state Gilbert-Elliott loss model with the state transition probabilities $1 - P_G$ and $1 - P_B$ for $P_G = \gamma$ and $P_B = \beta$. The symbol loss probabilities are specified by e_G and e_B where $e_G << e_B$.

$$P_k(n, m_k) \;=\; P_k(n, m_k, G) + P_k(n, m_k, B) \tag{6}$$

The layer k recursive probabilities of receiving m_k symbols from n transmitted symbols and winding up in the GOOD state $P(n, m_k, G)$ is given by

$$\begin{aligned} &P_k(n, m_k, G) \;= \\ &\quad e_{sym,G,k}\,[\gamma\,P_k(n-1, m_k, G) \\ &\qquad + (1-\beta)P_k(n-1, m_k, B)] \\ &\quad (1 - e_{sym,G,k})\,[\gamma\,P_k(n-1, m_k-1, G) \\ &\qquad\qquad + (1-\beta)P_k(n-1, m_k-1, B)] \end{aligned} \tag{7}$$

Similarly, the layer k recursive probabilities of receiving m_k symbols from n transmitted symbols and winding up in the BAD state $P(n, m_k, B)$ is given by

$$\begin{aligned} P_k(n, m_k, B) \; = \\ e_{sym,B,k} \left[(1-\gamma) \, P_k(n-1, m_k, G) \right. \\ \left. + \beta P_k(n-1, m_k, B) \right] \\ (1 - e_{sym,B,k}) \left[(1-\gamma) \, P_k(n-1, m_k - 1, G) \right. \\ \left. + \beta P_k(n-1, m_k - 1, B) \right] \end{aligned} \tag{8}$$

for $n \geq m_k > 0$ and the initial conditions

$$\begin{array}{lll} P_k(0,0,G) & = g_{ss} \; = \; \frac{1-\beta}{2-\gamma-\beta} \\ P_k(0,0,B) & = b_{ss} \; = \; \frac{1-\gamma}{2-\gamma-\beta} \\ P_k(1,0,G) & = e_{sym,G,k} \left[\gamma \, g_{ss} \; + \; (1-\beta) \, b_{ss} \right] \\ P_k(1,0,B) & = e_{sym,B,k} \left[(1-\gamma) \, g_{ss} \; + \; \beta \, b_{ss} \right] \end{array} \tag{9}$$

Utilizing Equation (6) along with Equation (7) and Equation (8) for the Gilbert-Elliott model, the residual symbol error rate or the probability of a block loss at layer k is given by

$$\Psi_k(n, t_{c,k}) = 1 \; - \sum_{i=n-t_{c,k}}^{n} P_k(n, i) \tag{10}$$

It is also important to note that utilizing the two-state Gilbert-Elliott model calls for changing Equation (1) in order to distinguish between the symbol error rates of the GOOD state and the BAD state. Assuming $N_{0,G}$ and $N_{0,B}$ respectively denote the one-sided spectral density of the white Gaussian noise in the GOOD state and the BAD state, the average received signal to noise ratio of the GOOD state and the BAD state at layer k are expressed as

$$\begin{array}{ll} \overline{SNR}_{G,k} & = \mathcal{E}[|\alpha|^2] \, \frac{E_{sym,k}}{N_{0,G}} \\ \overline{SNR}_{B,k} & = \mathcal{E}[|\alpha|^2] \, \frac{E_{sym,k}}{N_{0,B}} \end{array} \tag{11}$$

where $N_{0,G} << N_{0,B}$ and the other parameters are the same as in Equation (1).

C. The Layered Gauss-Markov Source Model

For the source coding analysis of this section, we utilize a layered Gauss-Markov source with a variance σ^2_{GM} and a correlation coefficient ρ. Relying on the discussion of [5] and utilizing such a model for a transform coder, the operational distortion-rate function $D_{o,k}$ of layer k can be expressed as

$$D_{o,k}(R_{s,k}) = \xi \, \sigma^2_{GM} \, (1-\rho^2)^{\frac{\eta-1}{\eta}} \, 2^{-2R_{s,k}} \tag{12}$$

where η is the block length of the transform coder, ξ is a constant depending on the quantizer utilized for the transform coefficients, and $R_{s,k}$ is defined previously. We note that the operational distortion-rate function of Equation (12) converges to the distortion-rate function of a Gauss-Markov source described as

$$D(R_s) = \sigma^2_{GM} \, (1-\rho^2) \, 2^{-2R_s} \tag{13}$$

when $\eta \to \infty$ and $\xi = 1$. We also note that the Gauss-Markov source of Equation (12) is reduced to a memoryless Gaussian source by setting $\rho = 0$. In our model, any symbol associated with an unrecovered block is replaced by the Gaussian mean, thereby introducing a distortion of σ^2_{GM}. Consequently, the distortion of layer k at the decoder is calculated by taking the average of block recovery and block loss distortions multiplied by their associated probabilities. Assuming a block loss probability of $\Psi_k(n, t_{c,k})$, the stand-alone distortion D_k of layer k is calculated as

$$\begin{aligned} D_k \; & = D_{s,k} + D_{v,k} \\ & = \; (1 - \Psi(n, t_{c,k})) \, D_{o,k} + \Psi(n, t_{c,k}) \, \sigma^2_{GM} \end{aligned} \tag{14}$$

where $\Psi_k(n, t_{c,k})$ can be calculated from Equation (10) in the case of utilizing the Gilbert-Elliott loss model. Next, we note that utilizing successive refinability implies an enhancement layer can only be decoded together with the base layer and all of the previous enhancement layers. Consequently, Equation (14) needs to be modified as

$$D_k \; = \; \Psi_k^{(r)} \, D_{o,k} + \Psi_k^{(l)} \, \sigma^2_{GM} \tag{15}$$

where the recursive probabilities $\Psi_k^{(r)}$ and $\Psi_k^{(l)}$ are defined as

$$\begin{aligned} \Psi_k^{(r)} \; & = \; (1 - \Psi(n, t_{c,k}))(1 - \Psi_{k-1}^{(r)}) \\ \Psi_k^{(l)} \; & = \; \Psi(n, t_{c,k}) + (1 - \Psi(n, t_{c,k})) \, \Psi_{k-1}^{(l)} \end{aligned} \tag{16}$$

with $\Psi_1^{(r)} = 1 - \Psi(n, t_{c,1})$ and $\Psi_1^{(l)} = \Psi(n, t_{c,1})$.

III. Power Optimization

We formulate the power optimization problem of a wireless layered system subject to distortion and rate constraints as

$$\min_{R_{s,k}, R_{c,k}, E_{sym,k}} \quad P_{Tot} \; = \; \sum_{k=1}^{K} (P_{s,k} + P_{c,k} + P_{t,k}) \tag{17}$$

$$\text{Subject To:} \quad D_k \; \leq \; D_{max,k} \tag{18}$$

$$R_{Tot} \; = \; \sum_{i=1}^{k} (R_{s,i} \; + \; R_{c,i}) \; \leq \; R_{max,k} \tag{19}$$

where $k = 1, \cdots, K$, $D_{max,1} > \cdots > D_{max,K}$, and $R_{max,1} < \cdots < R_{max,K}$. Having to deal with layered source coding, the distortion observed by a mobile device receiving layers 1 through k is calculated based on the aggregate source coding rates. Consequently, the operational distortion-rate function $D_{o,k}$ of layer k is approximated as

$$D_{o,k}(R_{s,k}) = \xi \, \sigma^2_{GM} \, (1-\rho^2) \, 2^{-2 \sum_{i=1}^{k} R_{s,i}} \tag{20}$$

We note that the optimization variables are the source coding rates of individual layers $R_{s,k}$, the channel coding rates of individual layers $R_{c,k}$, and the transmission symbol energy of individual layers $E_{sym,k}$. Different components of (17) are described below. The first power consumption component is associated with the layered source encoder utilizing a Gauss-Markov source. We express layer k power consumption of such a source encoder as a linear function of the encoder rate, i.e.,

$$P_{s,k}(R_{s,k}) \; = \; \epsilon_{s,k} \, (a_{s,k} \; + \; c_{s,k} R_{s,k}) \tag{21}$$

where $\epsilon_{s,k}$ is a scaling constant, $a_{s,k}$ and $c_{s,k}$ are the linear model constants associated with layer k. The second power consumption component is associated with the channel coder. According to [2], the power consumption of a Reed-Solomon $RS(n, m_k)$ encoder at layer k can be modeled as

$$P_{c,k}(R_{s,k}, R_{c,k}) = \epsilon_{c,k} \frac{m_k R_{c,k}}{b} \quad (22)$$

where $\epsilon_{c,k}$ is a scaling factor associated with layer k and b is the number of bits per symbol. Finally, the third power consumption component is associated with the transmitter. The total transmission power of layer k is given by

$$P_{t,k}(R_{s,k}, R_{c,k}, E_{sym,k}) = \epsilon_{t,k} \frac{E_{sym,k}}{b}(R_{s,k} + R_{c,k}) \quad (23)$$

where $\epsilon_{t,k}$ is the scaling factor of layer k that maps the radiated energy of layer k into the actual transmission power of a mobile device.

Similar to the discussion of [9], the constrained optimization problem of (17) along with the constraint sets (18) and (19) can be solved by relying on an iterative Sequential Quadratic Programming (SQP) technique [3] that allows for closely mimicking Newton's method the same way as it is done for an unconstrained optimization problem. In every iteration of SQP, the Lagrangian function defined as

$$\begin{array}{l} LG_P = \sum_{k=1}^{K}(P_{s,k} + P_{c,k} + P_{t,k}) \\ +\mu_1(D_1 - D_{max,1}) + \cdots + \mu_K(D_K - D_{max,K}) \\ +\mu_{K+1}(R_{s,1} + R_{c,1} - R_{max,1}) + \cdots \\ \quad +\mu_{2K}(\sum_{k=1}^{K}(R_{s,k} + R_{c,k}) - R_{max,K}) \end{array} \quad (24)$$

Further, the Hessian of the Lagrangian function defined as

$$\begin{array}{l} \nabla LG_P = [\frac{\partial LG_P}{\partial R_{s,1}}, \cdots, \frac{\partial LG_P}{\partial R_{s,K}}, \frac{\partial LG_P}{\partial R_{c,1}}, \cdots, \frac{\partial LG_P}{\partial R_{c,K}}, \\ \quad \frac{\partial LG_P}{\partial E_{sym,1}}, \cdots, \frac{\partial LG_P}{\partial E_{sym,K}}, \frac{\partial LG_P}{\partial \mu_1}, \cdots, \frac{\partial LG_P}{\partial \mu_{2K}}] \end{array} \quad (25)$$

is approximated using a quasi-Newton updating method. The result is then utilized to create a quadratic programming (QP) subproblem whose solution is used to form a search direction for a line search procedure. The procedure of extracting QP subproblem works based on linearizing the nonlinear constraints namely the set of constraints identified by (18). The QP subproblem can be solved making use of Karush-Kuhn-Tucker (KKT) necessary conditions for optimality. Defining

$$\Omega = \{R_{s,1}, \cdots, R_{s,K}, R_{c,1}, \cdots, R_{c,K}, E_{sym,1}, \cdots, E_{sym,K}\}$$

and assuming all of the terms have been replaced by the appropriate approximated terms, the KKT conditions at the optimum point Ω^* are described as

$$\begin{array}{l} \nabla LG_P(\Omega^*) = 0 \\ \mu_1^*(D_1^* - D_{max,1}) = \cdots = \mu_K^*(D_k^* - D_{max,K}) = 0 \\ \mu_{K+1}^*(R_{s,1}^* + R_{c,1}^* - R_{max,1}) = \cdots = \\ \quad \mu_{2K}^*(\sum_{k=1}^{K}(R_{s,k}^* + R_{c,k}^*) - R_{max,K}) = 0 \end{array} \quad (26)$$

where the superscript $*$ has been used to indicate the optimal values of the variables. The time complexity of the algorithm is $\mathcal{O}(I\, p\, d \log d)$ where p represents the number of parameter combinations, I indicates the number of iterations, and d indicates the degree of the estimation. We note that depending on the distortion requirements of each layer, the optimization problem may or may not have an answer. This is explained considering the complex nonlinear surface of the feasible region of the problem.

IV. Numerical Analysis

In this section, we numerically validate our analytical results. Before proceeding with the explanation of our numerical results, we note that we are solving our problem for both single and double transmit antenna wireless systems. In the case of a double transmit antenna system, we assume that the transmission is based on the space-time block codes of [1] and [14]. In addition, we assume that the slow fading wireless channel characterized by Rayleigh distribution is quasi-static and flat implying that the path gains are constant over a frame but vary from one frame to another.

We compare the results of a single transmit antenna system with those of a double transmit antenna system. In our experiments, we utilize a layered Gauss-Markov source with values $\xi = 1$, $\sigma_{GM}^2 = 1$, and $\rho = 0.9$ to represent a highly correlated source with a behavior close to a video source. Further, we allow unequal error protection of the layers. We set the number of layers to $k = 3$. The maximum allowable bit rates $\{R_{max,1}, R_{max,2}, R_{max,3}\}$ are respectively set at $\{2.4, 4.8, 7.2\}$. Allowing the parameter δ to vary in the interval $[0.8, 1.2]$, the maximum distortion values $D_{max,i}$ for $i \in \{1, 2, 3\}$ are set from Equation (13) with $R_s = i\,\delta$.

Further, we set a block length of $n = 222$ symbols for the RS coder with BPSK and QPSK modulations. We allow channel coding variables m_k to assume values from the discrete set $\{142, 152, 162, 172, 182, 192, 202\}$. We also set $N_{0,G} = 0.1\, N_{0,B}$ to distinguish between the GOOD state and the BAD state. The settings of the parameters of the Gilbert-Elliott model follow. The constants $\{\gamma, \beta\}$ are set to $\{0.99873, 0.875\}$ indicating a burst length $L_B = \frac{1}{1-\beta} = 8$ consistent with our previous work of [15]. We select the scaling factors $\{\epsilon_{s,k}, \epsilon_{c,k}, \epsilon_{t,k}\}$ as $\{1, 0.01, 1\}$ independent of the value of k.

Table I includes the set of the optimal values for the decision variables in a number of unequal error protection experiments with the above-mentioned settings. An investigation of the contents of Table I reveals a couple of interesting observations. First, it is observed that utilizing double transmit antennas consistently yields to a lower optimized power for the same quality of service. Second, the optimal value of the consumed power tends to increase as the value of δ increases indicating a lower distortion and a higher quality of service.

Additionally, an investigation of the optimal values of total power in an equal error protection scenario in which $m_1 = \cdots = m_K = m$ also reveals the advantage of utilizing double transmit antennas over a single transmit antenna. Table II shows the optimal values of the decision variables in a set of experiments utilizing BPSK modulation scheme with $\{R_{max,1}, R_{max,2}, R_{max,3}\} = \{1.6, 3.2, 4.8\}$, $\{D_{max,1}, D_{max,2}, D_{max,3}\} = \{0.0475, 0.0119, 0.0030\}$, and

TABLE I

OPTIMAL UNEQUAL ERROR PROTECTION RESULTS OF A SINGLE TRANSMIT ANTENNA FOLLOWED BY DOUBLE TRANSMIT ANTENNAS FOR BPSK MODULATION.

δ	0.8	0.9	1.0	1.1	1.2
$R^*_{s,1}$	1.54	1.54	1.01	1.11	1.21
$R^*_{s,2}$	0.91	0.28	2.06	1.96	1.86
$R^*_{s,3}$	0.001	0.95	0.001	0.30	0.61
$R^*_{c,1}$	0.86	0.86	0.57	0.63	0.68
$R^*_{c,2}$	0.51	0.16	1.16	1.10	1.05
$R^*_{c,3}$	0.0006	0.53	0.0006	0.17	0.35
$E^*_{sym,1}$	1.84	1.91	2.06	2.13	2.19
$E^*_{sym,2}$	1.93	2.22	1.93	2.02	2.11
$E^*_{sym,3}$	3.56	2.00	4.94	2.39	2.33
$Power^*$	333.65	338.31	342.59	347.46	352.30
$R^*_{s,1}$	1.54	0.91	1.54	1.11	1.21
$R^*_{s,2}$	0.88	1.81	0.47	1.96	1.86
$R^*_{s,3}$	0.001	0.001	1.01	0.25	0.55
$R^*_{c,1}$	0.86	0.51	0.86	0.62	0.68
$R^*_{c,2}$	0.49	1.02	0.27	1.11	1.05
$R^*_{c,3}$	0.0006	0.0006	0.57	0.14	0.31
$E^*_{sym,1}$	0.35	0.38	0.38	0.40	0.41
$E^*_{sym,2}$	0.37	0.36	0.42	0.38	0.40
$E^*_{sym,3}$	0.84	0.73	0.39	0.46	0.44
$Power^*$	327.42	330.89	334.43	337.91	341.45

other settings identical to what was mentioned above. We note that the optimal channel coding bit rates associated with the set of numbers in each column are calculated from $r^*_{c,k} = \frac{n-m}{m} R^*_{s,k}$. We observe that the optimal bit rate of source coding for the higher layers tends to decrease as the channel coding rate increases. This is justified by recalling the fact that the same levels of distortion can be achieved with lower power if a higher bit rate is assigned to lower layers. On the other hand, there is a tradeoff between the available bit rate of a layer and the channel coding rate. At the end of this section, we note that the results of QPSK are qualitatively similar and are omitted here due to lack of space.

V. CONCLUSIONS

In this paper, we presented a solution to the problem of power control in wireless systems utilizing multiple transmit antennas and successively refinable source coding. We provided an analysis of the underlying wireless system consisting of transmitting, channel, and receiving sides. Relying on our analysis, we formulated an optimization problem that was aimed at minimizing the total power consumption of a wireless system subject to a given QoS level and an overall available bit rate. Our formulation considered the power consumption components related to source coding, channel coding, and transmission of multiple transmit antennas. While our layered source coding analysis utilized a Gauss-Markov source, our channel coding analysis relied on a Rayleigh fading channel along with the Gilber-Elliott loss model. Finally, our transmission analysis

TABLE II

OPTIMAL EQUAL ERROR PROTECTION RESULTS OF A SINGLE TRANSMIT ANTENNA FOLLOWED BY DOUBLE TRANSMIT ANTENNAS FOR BPSK MODULATION.

m	162	172	182	192	202
$R^*_{s,1}$	1.01	1.01	1.01	1.01	1.01
$R^*_{s,2}$	1.32	1.47	1.61	1.76	1.90
$R^*_{s,3}$	0.77	0.65	0.54	0.43	0.35
$E^*_{sym,1}$	3.53	4.88	7.13	11.44	22.04
$E^*_{sym,2}$	3.44	4.68	6.74	10.65	20.13
$E^*_{sym,3}$	3.63	5.12	7.67	12.72	25.53
$Power^*$	347.81	352.35	359.91	374.36	409.58
$R^*_{s,1}$	1.01	1.01	1.01	1.01	1.01
$R^*_{s,2}$	1.33	1.47	1.61	1.76	1.90
$R^*_{s,3}$	0.74	0.61	0.49	0.39	0.29
$E^*_{sym,1}$	2.23	2.91	3.97	5.84	9.77
$E^*_{sym,2}$	2.17	2.79	3.76	5.42	8.87
$E^*_{sym,3}$	2.30	3.07	4.33	6.63	11.69
$Power^*$	341.90	343.96	347.31	353.28	365.79

used space-time block codes. We observed that the power optimization results of our multiple transmit antenna system were consistently better than the results of a comparable single transmit antenna system.

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