Rate Constrained Power Control in Space-Time Coded Fading Ad-Hoc Networks

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***Abstract*— Under aggregate data rate and loss constraints, we study the problem of power control for fading wireless ad-hoc networks accommodating space-time coded mobile nodes. Our study relies on modeling the underlying wireless channel with finite-state Markov chains and using Reed-Solomon channel coders to compensate for the temporally correlated loss observed in such networks. Our study shows that utilizing space-time coding techniques can reduce power consumption of ad-hoc networks under the given constraints. Further, we investigate the tradeoff between practicality and optimality by means of introducing centralized and decentralized power control schemes. We quantify the tradeoff by comparing different schemes together.**

***Index Terms*— Ad-Hoc Networks, Rayleigh Fading Channel, Markov Chain, Space-Time Processing, Power Minimization.**

I. INTRODUCTION

Wireless ad-hoc networks have received a major attention from the research community in the recent years. Popularity of such networks requires providing effective methods of coping with a variety of related issues. Addressing the tradeoff between power consumption and Quality of Service (QoS) under the presence of fading and temporally correlated loss in the wireless channel is an important such issue. This paper offers an integrated framework for studying the tradeoff between power consumption and achievable QoS in fading ad-hoc networks.

Among the rich set of literature articles, the followings are more closely related to our current discussion. Andersin et al. [2], Bambos et al. [3], Qiu et al. [10], and Ulukus et al. [16] proposed various iterative methods to maximize the minimum signal-to-interference ratio (SIR), to minimize total or individual power, or to maximize throughput under some kind of QoS constraint. Relying on Geometric Programming (GP), Chiang et al. [5] solved a set of resource allocation problems for QoS provisioning in wireless ad-hoc networks. Kandukuri et al. [9] solved a similar problem aimed at minimization of the outage probability in cellular networks under Rayleigh fading without QoS constraints. Hayajneh et al. [8] proposed a game-theoretic power control algorithm for wireless channels. Shah et al. [12] and Ramanathan et al. [11] investigated the issue of power control in wireless networks with the considerations of network topology.

The material presented in this paper addresses some important open areas related to our earlier work of [18]. In the latter article, we model the temporally correlated loss behavior observed in a wireless channel with a finite-state Markov chain. In order to compensate for the correlated loss effects of the fading channel represented in a finite-state Markov chain, we propose the use of Reed-Solomon (RS) channel coders. Utilizing an analysis of channel coding, we focus on a centralized resource allocation problem subject to power and loss constraints. However, our work of [18] does not consider the use of space-time coded mobile nodes and the associated potential improvements in the operation of ad-hoc networks. Further, it does not address the tradeoff between practicality and optimality either. Addressing practicality is important as implementing a centralized resource allocation scheme may become overhead prohibitive in a large size network.

Hence, the contributions of this work are in the following areas. First, we extend the analysis of [18] to include the effects of utilizing space-time coded mobile nodes. Next, we formulate and solve a power optimization problem subject to aggregate data rate and loss constraints. We also address the tradeoff between practicality and optimality. Our results show that utilizing space-time coded mobile nodes reduces the overall power consumption of ad-hoc networks under rate and loss constraints. They also show that depending on the underlying topology, significant power reductions may be resulted with a compromise in the accepted level of QoS.

The rest of this paper is organized as follows. Section II revolves around the underlying system analysis. In this section, we provide an analysis of channel modeling, calculation of symbol error rates for space-time coded mobile nodes, and the proposed channel coding scheme. In Section III, we formulate and solve our power optimization problem aimed at minimizing total transmission power subject to block loss probability, aggregate data rate, and maximum per link available powers. Section IV provides numerical results of our experiments validating our analysis under node mobility. Finally, Section V concludes this work.

II. SYSTEM ANALYSIS

In this section, we provide an analysis of the underlying communication system based on the characteristics of the fading wireless channel. The following subsections include a discussion of fading channel modeling with finite-state Markov chains, calculation of symbol error rates over the links associated with space-time coded mobile nodes, and the channel coding scheme proposed for compensating the effects of correlated loss observed over wireless links.

A. Finite-State Markov Chain Modeling of the Fading Channel

Our discussion starts with providing an analysis of the signal-to-interference-noise ratio for a fading channel described by the

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Rayleigh model. Consider n wireless links labeled $L_1, \ldots, L_n$, on which per symbol transmission powers are $P_1, \ldots, P_n$, respectively. The per symbol transmission power P_j is assumed to be equally distributed among M_j transmit antennas of link j. The number of receive antennas for link j is assumed to be N_j. $G_{ij}(t)$ represents the path gain in the absence of fading from the transmitter of link j to the receiver of link i at time t. $G_{ij}(t)$ captures factors such as path loss, shadowing, and antenna gain. $F_{ij}^{(m,n)}(t)$ is the fading factor between transmitting antenna m of link j and receiving antenna n of link i. Treating the paths between different pairs of transmit and receive antennas as independent ones, the power at the receiver of link i is given by

$$G_{ii}(t)\ \frac{P_i(t)}{M_i}\ \sum_{m=1}^{M_i} \sum_{n=1}^{N_i} F_{ii}^{(m,n)}(t) \tag{1}$$

Similarly, interfering signals from all of the other links on which P_j's ($i \neq j$) are transmitted are given by

$$\sum_{j \neq i} G_{ij}(t)\ \frac{P_j(t)}{M_j}\ \sum_{m=1}^{M_j} \sum_{n=1}^{N_i} F_{ij}^{(m,n)}(t) \tag{2}$$

The instantaneous signal-to-interference-noise ratio at time t for link i determines the quality of the received signal. It is defined as

$$SINR_i(t) = \frac{G_{ii}(t)\frac{P_i(t)}{M_i}\sum_{m=1}^{M_i}\sum_{n=1}^{N_i}F_{ii}^{(m,n)}(t)}{\sum_{j\neq i} G_{ij}(t)\frac{P_j(t)}{M_j}\sum_{m=1}^{M_j}\sum_{n=1}^{N_i}F_{ij}^{(m,n)}(t) + N_i n_i(t)} \tag{3}$$

noting that the power of white Gaussian noise signal $n_i(t)$ on link i is multiplied by N_i. In [18], we provide a modeling scheme of the Rayleigh fading channel with a finite-state Markov chain. We do so by partitioning the probability density function of the fading and specifying the average signal-to-interference-noise ratio in terms of various fading factors as well as noise expectations. Our modeling scheme relies on the assumptions that (1) the time shift correlations of fading factors over the same links are temporally correlated, (2) the time shift correlations of fading factors over different links are i.i.d, (3) the distribution of the white Gaussian noise is independent from the fading distributions, (4) F_{ij}'s have unit means so long as G_{ij}'s are appropriately scaled, and (5) the wireless channel varies slowly with respect to the symbol interval.

In our discussion, a finite-state Markov chain is described by a set of state transition probabilities and a set of per state symbol error rates. While the channel modeling scheme of our work can be applied to any number of states, we utilize the so-called 2-state Gilbert-Elliott Markov chain [7] as it provides a good balance between model accuracy and computation overhead. We recall that the Gilbert-Elliott model is represented by a GOOD and a BAD state. It is fully specified by two pairs of probabilities. The pair γ and β are associated with state transition probabilities and represent the probability of no state transition from the GOOD and the BAD state, respectively. The pair SER_G and SER_B with $SER_G << SER_B$ represent the symbol error rates in the GOOD and BAD state, respectively. In practice, the observed average burst length can be used to set the partitioning thresholds and consequently the parameters γ and β. As described in the next section, the parameters SER_G and SER_B can be specified in terms of average received signal-to-interference-noise ratios, modulation, and the number of transmit and receive antennas. We note that the average received signal-to-interference-noise ratios are derived from Equation (3) by taking the expectations of the numerator and denominator.

B. *Calculation of Space-Time Coded Symbol Error Rates*

Based on the discussion of [13], our work of [17] calculates closed-form expressions describing the symbol error rate of a space-time coded system in terms of the number of signal points in the constellation M and the average received signal-to-noise ratio. We carry out our calculations under the assumption of facing a slow fading Rayleigh channel and utilizing PSK modulation. We also note that our approach can be applied to other modulation schemes such as QAM. In what follows we use our previous results to capture per state symbol error rates of a wireless link connecting a pair of space-time coded mobile nodes.

First, we introduce the symbol error rate of a link associated with single transmit and N receive antenna mobile nodes using maximum ratio combining (MRC) as

$$SER = \tfrac{M-1}{M} - \tfrac{1}{\pi}\sqrt{\tfrac{\vartheta}{1+\vartheta}}\big\{\big(\tfrac{\pi}{2} + \tan^{-1}\xi\big)\textstyle\sum_{j=0}^{N-1}\binom{2j}{j}\tfrac{1}{[4(1+\vartheta)]^j} + \sin(\tan^{-1}\xi)\textstyle\sum_{j=1}^{N-1}\sum_{i=1}^{j}\tfrac{\sigma_{ij}}{(1+\vartheta)^j}[\cos(\tan^{-1}\xi)]^{2(j-i)+1}\big\} \tag{4}$$

where $\vartheta = SINR\sin^2(\frac{\pi}{M})$, $\xi = \sqrt{\frac{\vartheta}{1+\vartheta}}\cot\frac{\pi}{M}$, and $\sigma_{ij} = \frac{\binom{2j}{j}}{\binom{2(j-i)}{j-i}4^i[2(j-i)+1]}$. From Equation (4), one can calculate the symbol error rate of a link associated with single transmit single receive antenna nodes as well as a link associated with single transmit double receive antenna nodes by setting N to 1 and 2, respectively. Relying on a discussion of diversity gains, we also argue that the symbol error rate of the space-time block codes (STBCs) of [1] and [15] can be calculated from Equation (4) by proper mapping of the values of $SINR$. For example, the symbol error rate of a link associated with double transmit single receive antenna nodes can be calculated by replacing $SINR$ with $\frac{SINR}{2}$ and setting N to 2 in Equation (4). Similarly, the symbol error rate of a link associated with double transmit double receive antenna nodes can be calculated by replacing $SINR$ with $\frac{SINR}{2}$ and setting N to 4 in Equation (4). We note that the results of Equation (4) can be applied to the GOOD state and the BAD state in the Gilbert-Elliott loss model by replacing $SINR$ with $SINR_G$ and $SINR_B$, respectively.

Bringing the ideas of [6] in the context of wireless ad-hoc networks, the analysis of [18] relies on adaptive modulation as a mean of increasing maximum data rate that can be reliably transmitted over a fading channel. Adaptive modulation provides a number of parameters that can be adjusted according to the fading channel characteristics. The range of parameters includes constellation sizes, transmit power, symbol rate, and channel coding rate/scheme. Similar to the approach of [18], we propose the use of an adaptive modulation scheme to further increase the data rate of a wireless link. In this work, we are most interested in adjusting constellation sizes resulting in the determination of a set of per link data rates R_i as $R_i = \frac{1}{T}\log_2 M_i$ where $\frac{1}{T}$ is the baseband bandwidth.

C. Proposed Channel Coding Scheme

We propose the use of Reed-Solomon (RS) channel coders to compensate for temporally correlated loss effects of the wireless channel. An RS channel coder $RS(b,k)$ converts k symbols into a b-symbol block by appending $(b-k)$ parity symbols. Such a channel coder is able to correct as many as $t_C = \lfloor \frac{b-k}{2} \rfloor$ symbol errors in a block. Let $\varphi(b,k,G)$ and $\varphi(b,k,B)$ denote the probability of receiving exactly k symbols from b symbols and winding up in the GOOD and the BAD state of the Gilbert-Elliott model, respectively. The probability of receiving exactly k symbols from a b-symbol block for the Gilbert-Elliott model is given by

$$\varphi(b,k) \;=\; \varphi(b,k,G) + \varphi(b,k,B) \tag{5}$$

The recursive probabilities of receiving exactly k symbols from b transmitted symbols and winding up in the GOOD state and the BAD state are respectively given [18] by

$$\begin{aligned}\varphi(b,k,G) \;=&\\ &SER_G\,[\gamma\,\varphi(b-1,k,G) \;+\; (1-\beta)\varphi(b-1,k,B)]\\ &(1-SER_G)\,[\gamma\,\varphi(b-1,k-1,G)\\ &\qquad + (1-\beta)\varphi(b-1,k-1,B)]\end{aligned} \tag{6}$$

and

$$\begin{aligned}\varphi(b,k,B) \;=&\\ &SER_B\,[(1-\gamma)\,\varphi(b-1,k,G) \;+\; \beta\varphi(b-1,k,B)]\\ &(1-SER_B)\,[(1-\gamma)\,\varphi(b-1,k-1,G)\\ &\qquad + \beta\varphi(b-1,k-1,B)]\end{aligned} \tag{7}$$

for $b \geq k > 0$ and the initial conditions

$$\begin{aligned}\varphi(0,0,G) &= g_{ss} \;=\; \tfrac{1-\beta}{2-\gamma-\beta}\\ \varphi(0,0,B) &= b_{ss} \;=\; \tfrac{1-\gamma}{2-\gamma-\beta}\\ \varphi(1,0,G) &= SER_G\,[\gamma\,g_{ss} \;+\; (1-\beta)\,b_{ss}]\\ \varphi(1,0,B) &= SER_B\,[(1-\gamma)\,g_{ss} \;+\; \beta\,b_{ss}]\end{aligned} \tag{8}$$

If at least $b - t_C$ symbols are correctly received from b transmitted symbols, the whole block is recoverable. Hence, the block-loss probability is expressed as

$$\Psi = 1 - \sum_{k=b-t_C}^{b} \varphi(b,k) \tag{9}$$

III. Power Optimization Analysis

The discussion of this section revolves around formulating our power optimization problem and providing a solution to it. We minimize the sum of per link transmission powers subject to block-loss probability requirements, aggregate data rate provisioning, and maximum per link available powers. Our optimization problem is formulated as

$$\min_{P_i,\,M_i} \qquad P_{total} \;=\; \sum_{i=1}^{n} P_i \tag{10}$$

$$Subject\,To: \qquad \Psi_i \leq \Psi_{i,ub} \quad \forall i \tag{11}$$

$$\sum_{i=1}^{n} R_i \geq R_{lb} \tag{12}$$

$$P_{i,lb} \leq P_i \leq P_{i,ub} \quad \forall i \tag{13}$$

where per link transmission powers P_i's and signal point constellation sizes M_i's are the decision variables. The objective function (10) is to be optimized over all feasible per link powers and constellation sizes. The three sets of constraints are enforced to assure maximum block loss probability of the channel coder, minimum link data rate, and maximum available system powers. We note that the formulation of our problem can be applied either to an overall topology or on a per node basis with a sub-topology of links attached to the node. While the former case represents a centralized problem, the latter case represents a decentralized problem. In the latter case, the sum of the powers of the links using a given node as their transmitting node is minimized subject to a set of constraints. Similar to the objective function, the set of constraints are only applied to the links using the given node as their transmitting node.

In [4], the authors provide a discussion of iteratively solving quadratic estimations of a constrained optimization problem relying on Sequential Quadratic Programming (SQP) and line search methods. In SQP, Karush-Kuhn-Tucker (KKT) conditions represent necessary conditions for optimality. We propose using SQP to solve the power optimization problem formulated by (10) along with the constraint sets (11), (12), and (13). We note that the time complexity of solving the problem of (10) utilizing SQP is $\mathcal{O}(I\,q\,\log q)$ where I indicates the number of iterations and q indicates the degree of the quadratic estimation. For moderate values of I, the complexity results are low compared to other recursive optimization approaches.

IV. Mobility Experiments

In this section, we report the results of our mobility experiments utilizing both centralized and decentralized schemes proposed in the previous section. We note that we are solving our QoS-constrained power optimization problem in ad-hoc networks accommodating space-time coded mobile nodes. We consider two cases in which a mobile node is either equipped with one or two antennas. In the case of a double transmit antenna mobile node, we assume that two signals are transmitted simultaneously from the two antennas at each time slot using STBCs of [1] and [15]. In addition, we assume that the slow fading wireless channel characterized by a Rayleigh distribution is quasi-static and flat implying that the fading factors are constant over a symbol but vary independently from one symbol to another. It is also important to note that we assume the channel state information (CSI) is unknown at the encoder of the transmitting mobile node.

We apply our results to a small ad-hoc network topology as illustrated in Fig. 1. The network consists of mobile nodes $A, B, C, D, E,$ and F, along with 8 links L_1 through L_8. Each link can act both as a transmitter and a receiver. We also assume that a node can simultaneously transmit on multiple links by splitting its power on the outgoing links. Originally, the topology represents a symmetric topology with horizontal and vertical line segments of 10m each. By geometry the distance of the single hops L_3 and L_6 is $10\sqrt{2}$m. Similarly, the distance of the single hops L_7 and L_8 is $10\sqrt{5}$m. In our experiments, we allow node A to move across the horizontal axis x both toward and away from node F. We indicate the position of node A from a reference point by x. We select the reference point to be the middle of vertical line connecting nodes D and E. Hence, the original position of node A is indicated by $x = 20$. We consider four different scenarios: (1) the mobile nodes B, C, and F are single antenna nodes while the rest are double antenna nodes, (2) The mobile nodes B and C are single antenna nodes while the other nodes are double antenna nodes, (3) node F has a single antenna and the rest of the nodes have double antennas, and (4) all of the nodes have double antennas. In our experiments,

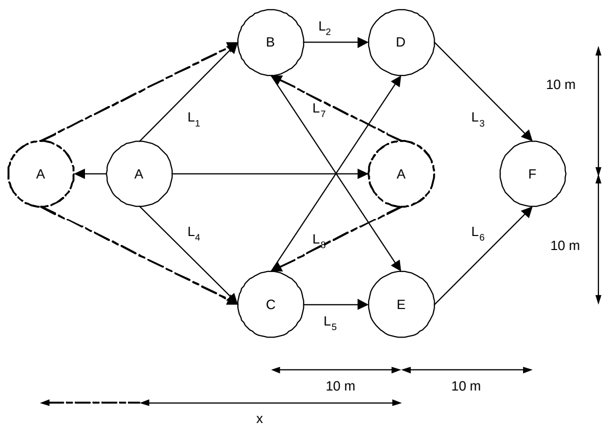

Fig. 1. An illustration of the network topology used in the simulation task.

the lower and upper regulatory power bounds are set at $0.001W$ and $1W$, respectively. The expected value of the noise power is assumed to be $E_n = 10\mu W$. All nodes are using $RS(31, 15)$ coders and adaptive M-PSK modulation representing a symbol with $log_2 M_i$ bits per link. The baseband bandwidth for each link is $\frac{1}{T} = 100KHz$ and the target aggregate data rate is $1.6Mbps$. We set a maximum allowable block-loss probability of 0.005. The gains for each link are computed as $G_{ii} = \frac{1}{d_{ii}^4}$ and $G_{ij} = \frac{\eta}{d_{ij}^4}$ for $i \neq j$, where d_{ij} represents propagation path length from the transmitter of link j to the receiver of link i. The factor η can be viewed as the power falloff with frequency in an FDMA system, or the spreading gain in a CDMA system. It is set as $\eta = 0.005$ in our experiments. The channel is assumed to introduce an average burst length of 32 resulting in state transition probabilities of $\{\gamma, \beta\} = \{0.99873, 0.9965\}$ in the case of partitioning a single transmit single receive antenna configuration. In order to comply with the notion of fairness, we keep the partitioning thresholds the same in the case of other antenna configurations. We set $SINR_G = 10SINR_B$ to distinguish between the GOOD and BAD state. The gain matrix G is an 8×8 matrix. The gains for G_{12}, G_{17}, G_{23}, G_{45}, G_{48}, G_{56}, G_{76}, and G_{83} are set to 0 since we assume a node cannot transmit and receive at the same time. The gain matrix is represented in the form of

$$G = [G_L | G_R] \tag{14}$$

The matrix G_L appears in the following form.

$$\begin{bmatrix} 1/((x-10)^2+100)^2 & 0 & \eta/100^2 & \eta/((x-10)^2+100)^2 \\ \eta/(x^2+100)^2 & 1/100^2 & 0 & \eta/(x^2+100)^2 \\ \eta/(x+10)^4 & \eta/500^2 & 1/200^2 & \eta/(x+10)^4 \\ \eta/((x-10)^2+100)^2 & \eta/400^2 & \eta/500^2 & 1/((x-10)^2+100)^2 \\ \eta/(x^2+100)^2 & \eta/500^2 & \eta/400^2 & \eta/(x^2+100)^2 \\ \eta/(x+10)^4 & \eta/500^2 & \eta/200^2 & \eta/(x+10)^4 \\ \eta/(x^2+100)^2 & \eta/500^2 & \eta/400^2 & \eta/(x^2+100)^2 \\ \eta/(x^2+100)^2 & \eta/100^2 & 0 & \eta/(x^2+100)^2 \end{bmatrix}$$

Further, the matrix G_R appears in the following form.

$$\begin{bmatrix} \eta/400^2 & \eta/500^2 & 0 & \eta/400^2 \\ \eta/500^2 & \eta/400^2 & \eta/100^2 & \eta/500^2 \\ \eta/500^2 & \eta/200^2 & \eta/500^2 & \eta/500^2 \\ 0 & \eta/100^2 & \eta/400^2 & 0 \\ 1/100^2 & 0 & \eta/500^2 & \eta/100^2 \\ \eta/500^2 & 1/200^2 & \eta/500^2 & \eta/500^2 \\ \eta/100^2 & 0 & 1/500^2 & \eta/100^2 \\ \eta/500^2 & \eta/400^2 & \eta/100^2 & 1/500^2 \end{bmatrix}$$

Note that matrix G is represented in the form above merely to adhere to the two column paper format.

First, we focus on our proposed centralized scheme. Fig. 2 shows the curves of optimal total power versus x the position of mobile node A utilizing our centralized scheme. The figure includes four curves illustrating the optimal power of scenarios (1) through (4) described above.

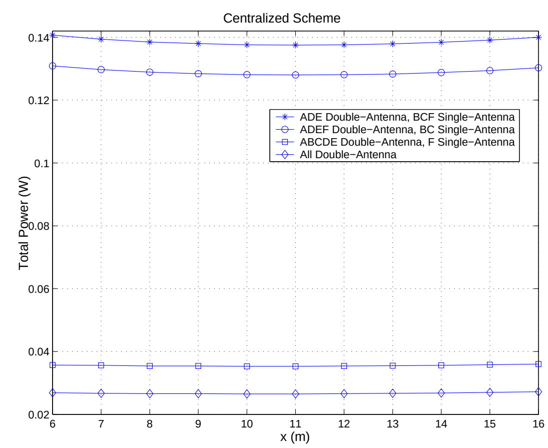

Fig. 2. Centralized optimal curves of total power versus x.

The first interesting observation is the fact that all of the four curves depicted in the figure are in the form of convex curves. While for the small values of x interference from other nodes increases total consumed power, for the large values of x total consumed power is increased due to the loss of signal strength. The curves show that total consumed powers are at their minimum levels when the value of x represents the position of node A approximately at $x = 11$m. The main observation when comparing the results of the figure is the fact that the transmission power of a mobile node over a link is reduced if the transmitting and receiving mobile nodes are equipped with a larger number of antennas. As the result, the power consumption of scenarios (1), (2), (3), and (4) are in the descending order.

Next, we focus on our proposed decentralized scheme and compare its results with those of our centralized scheme. We argue that our decentralized scheme provides a practical alternative to our centralized scheme at the cost of sub-optimality.

Fig. 3 compares the centralized and decentralized curves of total consumed power versus x the position of mobile node A.

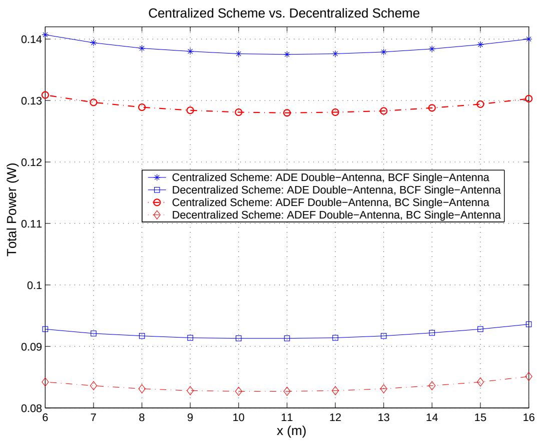

Fig. 3. A comparison of the results of centralized and decentralized schemes. The curves indicate total optimal consumed power versus x the position of mobile node A.

TABLE I

THE TABLE OF PER LINK AVERAGE MEASURED RESULTS OF Ψ_i WITH x MOVING IN THE RANGE OF $[6, 16]$M.

	Link	$\Psi_i\ (C)$	$\Psi_i\ (D)$
Scenario (1)	$\{L_1, L_4\}$	0.0050	0.0054
	$\{L_2, L_5\}$	0.0050	0.0051
	$\{L_3, L_6\}$	0.0050	0.0052
	$\{L_7, L_8\}$	0.0050	0.0091
Scenario (2)	$\{L_1, L_4\}$	0.0050	0.0052
	$\{L_2, L_5\}$	0.0050	0.0051
	$\{L_3, L_6\}$	0.0050	0.0060
	$\{L_7, L_8\}$	0.0050	0.0089

The mobile nodes are associated with scenarios (1) and (2) described above. As observed from the figure, the results of the decentralized scheme lead to a lower overall power consumption compared to their centralized counterpart. The results are justified considering the fact that the $SINR$ approximations of the decentralized scheme only take into consideration the interference factors from the nodes within one hop. Since the power components are calculated only with a consideration of local interference factors, they introduce actual inferior measured metrics of QoS. Table I illustrates the average measured results of Ψ_i of the associated scenarios in the case of centralized and decentralized schemes. In the case of decentralized scheme, per link data rate constraints are equal and sum up to an aggregate data rate of $1.6 Mbps$. Comparing the results, we observe while the data rate constraints are always active, the block loss probability difference between centralized and decentralized schemes for scenarios (1) and (2) are both in the range of $[1.9608\%, 45.0549\%]$. The difference in the similar quantity measure for scenarios (3) and (4) is in the range of $[1.9608\%, 56.1404\%]$. The results reveal that the use of decentralized scheme leads to (1) lower consumed power, (2) higher block loss probability, and (3) less complexity compared to the use of of centralized scheme.

We end this section by commenting on our complexity results. We have observed that an average of 20 and no more than 30 iterations are required for convergence of the centralized algorithm. The numbers in the case of decentralized algorithm are 3 and 5 , respectively. Further, we have observed that utilizing a 3-state Markov chain lowers the total consumed power compared to the case of a 2-state Markov chain, at the cost of a higher overhead of calculation.

V. Conclusion

In this paper, we examined the effects of utilizing space-time coded mobile nodes on reducing total power consumption in Rayleigh fading wireless ad-hoc networks. Relying on the modeling of fading channels with finite-state Markov chains, closed-form expressions for the symbol error rates of space-time coded mobile nodes, and the use of Reed-Solomon channel coding, we formulated and solved a power optimization problem subject to data rate and loss constraints. We investigated the tradeoff between practicality and optimality by providing a pair of centralized and decentralized solutions to our optimization problem. Our experimentations under mobility showed that depending on the network topology, the decentralized approach might provide a scalable solution at the cost of sub-optimality.

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