

Optimizing Control Overhead for Power-aware Routing in Wireless Networks

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Abstract—We analyze the tradeoff between the amount of signaling overhead incurred in path selection in a MANET with time-varying wireless channels and the application-level goodput and end-to-end power expended on the selected path. Here, increased overhead increases the accuracy of the link-state estimates used in path selection but decreases the amount of bandwidth available for application use. We develop an information-theoretic, bounding approach to quantify the signaling overhead. Specifically, we investigate (i) the time granularity at which link state is sampled and communicated, and (ii) the minimum number of bits needed to encode this link state information, such that the expected power consumption within a sampling interval is minimized subject to a fixed source-destination goodput constraint. We formulate an optimization problem that provides a numerically computable solution to these questions, and quantitatively demonstrate that short sampling intervals incur significant overhead while long intervals fail to take advantage of the temporal correlation in link state. Additionally, we find that using a small number of bits per sample do not provide sufficient information about the network while using too many bits provide little additional information at the expense of increased overhead. Our work can be used by network operators as a tool to determine parameters such as the optimal state update frequency and the number of bits per sample.

I. INTRODUCTION

The overhead of gathering state/control information (e.g., link states, node locations, queue lengths) can be significant in a mobile ad-hoc wireless network (MANET) when bandwidth is limited and network structure and state may change frequently. In such dynamic scenarios, it is still advantageous to collect state information, provided that this information leads to better decisions that more than compensate for the additional overhead incurred. For example, the decrease in available path bandwidth as a result of state gathering overhead may be more than compensated for by the choice of better paths for routing data packets. Efficient bandwidth use is not the only metric of concern in ad hoc networks; since nodes are typically battery powered, minimizing power consumption is also important.

Understanding the tradeoff between the cost incurred in state information collection in a network and the resulting performance is a fundamental, yet largely unexplored problem. In this paper, we analyze this tradeoff between the amount of state information collected (at what precision?, how often?) and overhead incurred, and the resulting performance in wire-

less networks while providing goodput guarantees. We develop an information-theoretic, bounding approach to analyze the tradeoff between the amount of signaling overhead incurred in path selection in a MANET with time-varying wireless channels and the application-level goodput and end-to-end power expended on the selected path.

We consider a network of n nodes with multiple source-destination pairs. We assume each source has m disjoint paths to the destination with k links on each path and that time is divided into intervals. At the beginning of every interval, each source collects ‘noisy’ estimates about the links in the network. By ‘noise’ we refer to the quantization error arising from finite precision representation of link states. The link state estimates in our model characterize the (time-varying) effect of shadowing on the received power.

We use the information-theoretic rate-distortion approach to quantify the noise in the link measurements - as we use more bits to encode time-varying link state, the fidelity of the estimates increase, but the control overhead also increases. Moreover, we assume each source also desires to achieve a fixed amount of goodput, which is defined as the total throughput (including control and data) minus the control overhead. The source selects a path i among the m paths such that the expected power consumed in that interval is minimized. The problem can be then stated in the following manner.

At what time granularity should links be sampled and at what rate (bits) should link values be encoded such that the expected power consumed in any interval is minimized subject to a fixed source-to-destination goodput constraint? We formulate an optimization problem which provides a numerically computable solution to these questions. The optimization problem takes as input the desired goodput, and leverages the distribution and autocorrelation of the shadowing process to determine the optimum value of the sampling interval and the number of bits per sample such that minimum power is consumed. Our optimization problem is solved off-line and provides network operators a tool for determining optimal operating points (state update frequency, number of bits per sample).

As expected, our evaluation quantitatively demonstrates that short sampling intervals incur significant overhead while long intervals fail to take advantage of the temporal correlation in link state. We also observe that using a small number bits per

sample do not provide sufficient information about the network while using too many bits provides little additional information at the expense of increased overhead. Additionally, we simulate a network with varying link states and compare the performance of the numerical and simulation results.

The rest of paper is organized as follows. We discuss related work in Section II. In Sections III and IV we describe our network model and the optimization problem respectively. We then provide a solution for the optimization problem in Sections V and VI. We present the numerical and simulation results in Sections VII and VIII respectively and finally conclude the paper in Section IX.

II. RELATED WORK

Most prior work has adopted simulation-based techniques to study the overhead of routing protocols in mobile wireless networks [1], [2]. Simulation has been used to study the performance of AODV and OLSR protocols in both VANETs [1] and MANETs [2]. Viennot *et. al* [3] perform a simple analysis of the control traffic for reactive and proactive protocols in MANETs considering parameters such as the average degree per node, the average number of routes created/sec and then compare analytical and simulation results for AODV, DSR and OLSR.

Theoretical studies characterizing the overhead of routing protocols in MANETs has been done by Abouzeid *et. al* [4], [5], [6], [7]. Zhou and Abouzeid [4] mathematically analyze the overhead of the reactive routing protocols and estimate the overhead associated with route discovery and route failure. They validate their numerical results via simulations of regular and random topologies. Information-theoretic techniques have been used to obtain lower bounds on memory requirements and routing overhead for hierarchical proactive routing in mobile ad hoc networks in [5]. The tradeoff between network properties such as connectivity, unpredictability and resource contention and state (control or data or both) information collection has been studied by Manfredi *et. al* [8].

Our work is closest to [7] where the authors use rate-distortion techniques (an information-theoretic approach) for analyzing the protocol overhead of link state MANET routing. They derive lower bounds on the minimum bit-rate at which a node must receive link state information in order to route data packets with a guaranteed delivery ratio. We differ from the above mentioned works because we consider the path selection problem and analyze the tradeoff between the signaling overhead (state update frequency and the number of bits per sample) and power consumption in time-varying channels while providing goodput guarantees.

Power consumption in wireless networks is also a well explored field [9], [10]. In [9] the authors consider the problem of joint routing, scheduling and power control in wireless networks and provide an approximate algorithm with performance guarantees to address it. Liu *et.al* [10] study the optimal power allocation scheme which maximizes the throughput with delay and average power consumption constraints. The primary difference between existing literature on power optimization and our work is that we model state gathering overhead/costs and are interested in determining the optimal sampling frequency

and number of bits for encoding samples so as to minimize the power dissipation while maintaining a fixed goodput.

III. NETWORK MODEL

In this section we describe our network model and assumptions. We consider a network of n nodes with multiple source-destination pairs where each source has m disjoint paths to the destination with k links on each path. We assume time is divided into intervals of duration T_s and at the beginning of every interval, each source collects ‘noisy’ estimates about the links in the network.

In our model these link state estimates characterize the (time-varying) effect of shadowing on the received power. Shadowing is assumed to be a lognormally distributed random process (in dB it is normally distributed) [11]. Consider any sampling interval and let t be a time of interest in that interval, $0 \leq t < T_s$. Let us consider the i^{th} path and the j^{th} link along this path at some time t .

Let $L_{ij}(t)$ be the lognormal shadowing process and $X'_{ij}(t) = 10 \log_{10} L_{ij}(t)$ be its value in dB. $X'_{ij}(t)$ is assumed to be a stationary Gaussian random process with mean $\mu = 0$ and autocorrelation function $R_{X'}(\tau) = \sigma'^2 e^{-\lambda\tau}$ [12]. The autocorrelation coefficient function ($\rho'(\tau)$) for any stationary random process $X'(t)$ may be defined as $\rho'(\tau) = \frac{R_{X'}(\tau) - \mu^2}{R_{X'}(0) - \mu^2}$. Thus for the shadowing process, the autocorrelation coefficient function is given by : $\rho'(\tau) = e^{-\lambda\tau}$.

For ease of analysis we express $\ln L_{ij}(t) = \frac{\ln 10}{10} X'_{ij}(t) = X_{ij}(t)$ replacing the logarithm to base 10 with the natural logarithm. Hence, $X_{ij}(t)$ is also Gaussian random process with mean 0 and autocorrelation function $R_X(\tau) = \sigma^2 e^{-\lambda\tau}$ where $\sigma^2 = (\frac{\ln 10}{10})^2 \sigma'^2$. Therefore, the autocorrelation coefficient function ($\rho(\tau)$) of $X(t)$ is given by $\rho(\tau) = \rho'(\tau)$. The correlation of $X_{ij}(t)$ indicates how the link state varies during the sampling interval, given its value at the beginning of the sampling interval. Knowledge of the correlation is essential for computing the expected power expended in an interval.

At the beginning of the sampling interval the source receives $\hat{X}_{ij}(0)$, which are ‘noisy’ estimates of $X_{ij}(0)$. As $X_{ij}(0)$ are drawn from a continuous distribution, encoding them exactly will require an infinite number of bits. The ‘noise’ therefore corresponds to the quantization error and thus $\hat{X}_{ij}(0)$ are finite precision representation of $X_{ij}(0)$. The number of bits used to encode the values of $X_{ij}(0)$ determines the closeness of $\hat{X}_{ij}(0)$ to $X_{ij}(0)$; thus, the inaccuracy in $\hat{X}_{ij}(0)$ decrease as more bits are used for encoding. If ϵ is the noise or quantization error then, $\hat{X}_{ij}(0) = X_{ij}(0) + \epsilon$.

We model ϵ as Gaussian noise with mean 0 and variance σ_e^2 [13]. We consider that all the link state values are encoded together and sent to the source. We use rate-distortion techniques [14] to upper bound σ_e^2 . In particular, define the distortion as the squared-error distortion, $d(x, \hat{x}) = (x - \hat{x})^2$. Then $\sigma_e^2 = E[(\hat{X}_{ij}(0) - X_{ij}(0))^2] \leq D$. The rate distortion function $R(D)$ for any $N(0, \sigma^2)$ source with squared-error distortion is given in [14]:

$$R(D) = \begin{cases} \frac{1}{2} \log_2 \frac{\sigma^2}{D} & 0 \leq D \leq \sigma^2 \\ 0 & D > \sigma^2 \end{cases} \quad (1)$$

Equation (1) thus represents the minimum number of bits required to encode each shadowing sample. It is also clear that $\hat{X}_{ij}(0)$ is a Gaussian random variable with mean 0 and variance σ_D^2 given by $\sigma_D^2 = \sigma_e^2 + \sigma^2$.

We assume that the path loss and thus the distance between any two pairs of nodes in the network is the same. Later in section VI we discuss how to relax this assumption.

IV. MINIMUM POWER PROBLEM

In this section we describe the *Minimum Power Problem*. Each source desires a goodput G . Let C_b and C_t be the control overhead and the overall throughput (combined control and data) respectively. Therefore we have $C_t = G + C_b$. At the beginning of each sampling interval, the source collects noisy link state estimates. The source desires to minimize the expected power spent in any interval to achieve goodput G . Based on the noisy link state estimates collected, the source calculates the expected power consumed along each of the M paths to the destination in that sampling interval. It then selects the path i for which the expected power consumed is least.

The goal of the *Minimum Power Problem* is to determine T_s and D such that over all possible instantiations of link estimates the expected power consumed (for transmitting both control and data) in any sampling interval to achieve a goodput requirement G is minimized.

Let Q_i be the expected power dissipated along the i^{th} path in a sampling interval, given the sampling interval T_s , the distortion D and the link state estimates $\hat{X}_{ij}(0)$ at the beginning of the interval. The source selects the path which dissipates the minimum expected power in the sampling interval and thus the *Minimum Power Problem* can be formally stated as,

$$\text{Objective: } \min_{T_s, D} \mathbb{E}[\min_i Q_i]$$

subject to the constraint:

$$C_t - C_b = G$$

V. POWER CONSUMPTION AND CONTROL OVERHEAD

In this section, we begin by modeling the transmit power expended along each path needed to achieve a fixed throughput during a sampling interval. We model the control overhead as a function of the total number of links in the network and the rate distortion function. These models for power, control overhead and shadowing are then used to obtain an approximate solution to the *Minimum Power Problem* in Section VI.

A. Power Consumption

The transmitted power $P_i(t)$ along the i^{th} path at time t to achieve a total throughput C_t (data and control) is obtained by summing the per-link power of each hop. Let d , W and B denote the distance between any two nodes, the transmission rate at any node and the available channel bandwidth in Hz respectively. Further consider a reference distance d_0 and let $P_t(d_0)$ and $P_r(d_0)$ be the transmit and received power between two nodes separated by d_0 . Shannon's formula [14] relates the transmission rate, the shadowing, the AWGN and the power.

There is a subtle point to be noted here. Although the transmission rate is W , the source can only achieve a lower throughput C_t , as the wireless medium is a shared resource - if multiple nodes transmit together, interference and packet loss

can occur. We assume that there is a scheduling algorithm that determines the time periods during a sampling interval when each source gets the opportunity to transmit. Each source transmits for only a fixed fraction of time during a sampling interval, e.g., it is allocated a fixed number of transmission slots in an interval. Let T_1 be the amount of time a source transmits in an interval of duration T_s .

We abstract away the scheduling details and define the scheduling factor as $S = \frac{T_1}{T_s}$. S depends on the scheduling algorithm and the number of nodes and is a parameter in our model. The details are available in [15]. Further, we consider a MANET with fast moving nodes such that C_t is much smaller than W . We also note that any arbitrary value of C_t is not achievable, e.g., the achievable C_t is bounded by results such as the Gupta-Kumar result [16].

Using the above model, the total power $P_i(t)$ expended along the i^{th} path obtained as the additive sum of the per-link power of each hop is given by

$$P_i(t) = \sum_{j=1}^k P_{ij}(t) = \sum_{j=1}^k \frac{2^{C_t/SB} - 1}{L_{ij}(t)} SFN_0 \quad (2)$$

where N_0 is the noise, $F = \frac{P_t(d_0)}{P_r(d_0)} \left(\frac{d}{d_0}\right)^\alpha$ and α is the path loss exponent.

B. Control Overhead

Following [7], we model the minimum overhead for gathering link state information as,

$$C_b = \frac{n(n-1)}{2} \frac{R(D)}{T_s} \quad (3)$$

The rationale behind this abstract model is that the total number of links must be less than $\frac{n(n-1)}{2}$ (the total number of links is $O(n^2)$), and a source must know the state of all network links to compute its best path to the destination. Hence, following [7] $\frac{n(n-1)}{2} \frac{R(D)}{T_s}$ represents the minimum control overhead.

VI. SOLVING THE OPTIMIZATION PROBLEM

In this section we approximately solve the *Minimum Power Problem*. All results used in this section are available in our technical report [15]. We begin by expressing $P_i(t)$ (2) as:

$$P_i(t) = \sum_{j=1}^k CY_{ij}(t) \quad (4)$$

where $C = (2^{C_t/SB} - 1)SFN_0$ and $Y_{ij}(t) = \frac{1}{L_{ij}(t)}$. Therefore, $Y_{ij}(t)$ is also a lognormal random process and we have $\ln Y_{ij}(t) = -X_{ij}(t)$.

Recall that Q_i is the expected power consumed along the i^{th} path in a sampling interval, given the sampling duration T_s , the distortion D and the link state estimates $\hat{X}_{ij}(0)$. Note that the centralized solution to the optimization problem only has $\hat{X}_{ij}(0)$'s available to it and not $\hat{X}_{ij}(0)$. Q_i can be formally expressed as,

$$Q_i = \frac{1}{T_s} \int_0^{T_s} \mathbb{E}[P_i(t) | \hat{X}_{i1}(0) \hat{X}_{i2}(0) \dots \hat{X}_{ik}(0); T_s, D] dt \quad (5)$$

Note that T_s and D are model parameters and are not random variables: we thus omit them while expressing conditional expectations. The expression for Q_i can be rewritten as,

$$Q_i = \frac{1}{T_s} \int_0^{T_s} \mathbb{E}[\mathbb{E}[P_i(t)|X_{i1}(0), \dots, X_{ik}(0)] | \hat{X}_{i1}(0), \dots, \hat{X}_{ik}(0)] dt \quad (6)$$

The above simplification can be done because given $X_{ij}(0)$, $P_i(t)$ is independent of $\hat{X}_{ij}(0)$, i.e., the underlying process itself does not depend on the observation $\hat{X}_{ij}(0)$. We first determine $H_i = \mathbb{E}[P_i(t)|X_{i1}(0), \dots, X_{ik}(0)]$ which can be done in the following way (7). At any given time t , $X_{ij}(t)|X_{ij}(0)$ is a Gaussian random variable with mean $\mu_x(t) = \rho(t)X_{ij}(0)$ and variance $\sigma_x^2(t) = \sigma^2(1 - \rho^2(t))$ [15]. Hence at any given time t , $Y_{ij}(t)|X_{ij}(t)$ is a lognormal random variable with mean $e^{-\mu_x(t) + \frac{\sigma_x^2(t)}{2}}$ [15].

$$\begin{aligned} H_i &= C \sum_{j=1}^k \mathbb{E}[Y_{ij}(t)|X_{i1}(0), \dots, X_{ik}(0)] dt \\ &= C \sum_{j=1}^k A(t) e^{-\rho(t)X_{ij}(0)} dt \end{aligned} \quad (7)$$

where $A(t) = e^{\frac{\sigma^2}{2}(1-\rho^2(t))}$. Substituting (7) in (6) we have,

$$\begin{aligned} Q_i &= \frac{C}{T_s} \sum_{j=1}^k \int_0^{T_s} \mathbb{E}[A(t) e^{-\rho(t)X_{ij}(0)} | \hat{X}_{ij}(0)] dt \\ &= \frac{C}{T_s} \int_0^{T_s} A(t) e^{\frac{\rho^2(t)\sigma^2}{2}} \sum_{j=1}^k e^{-\rho(t)\hat{X}_{ij}(0)} dt \end{aligned} \quad (8)$$

Equation (8) uses the fact that the quantization error ϵ is independent of $\hat{X}_{ij}(0)$. Moreover, at any given time t , $\rho(t)\epsilon$ is a Gaussian random variable with mean 0 and variance $\rho^2(t)\sigma_\epsilon^2$. Therefore, at any given time t , $e^{\rho(t)\epsilon}$ is a lognormal random variable with mean $e^{\frac{\rho^2(t)\sigma_\epsilon^2}{2}}$ [15].

We would like to further simplify the expression for Q_i . We approximate the sum of lognormal random variables by a lognormal random variable [15]. In (8), at any given time t , $Y'_{ij}(t) = e^{-\rho(t)\hat{X}_{ij}(0)}$ is a lognormal random variable with mean $\mu_{y'}(t) = e^{\frac{\rho^2(t)\sigma_D^2}{2}}$ and variance $\sigma_{y'}^2(t) = (e^{\rho^2(t)\sigma_D^2} - 1)e^{\rho^2(t)\sigma_D^2}$. Therefore, $Y'_i(t) = \sum_{j=1}^k Y'_{ij}(t)$ is approximated by a lognormal random variable with mean $\mu_1(t) = k\mu_{y'}$ and variance $\sigma_1^2(t) = k\sigma_{y'}^2$. Let $Z_i(t)$ be the Gaussian variable corresponding to $Y'_i(t)$. We can express its variance $\sigma_z^2(t) = \ln \left[\frac{e^{\rho^2(t)\sigma_D^2} - 1}{k} + 1 \right]$ and mean $\mu_z(t) = \ln k + \frac{\rho^2(t)\sigma_D^2}{2} - \frac{\sigma_z^2(t)}{2}$ [15]. Further, let $A_1(t) = A(t) e^{\frac{\rho^2(t)\sigma_\epsilon^2}{2}} = e^{\frac{\rho^2(t)\sigma_\epsilon^2 + \sigma^2(1-\rho^2(t))}{2}}$. We then express (8) as,

$$Q_i = \frac{C}{T_s} \int_0^{T_s} A_1(t) \sum_{j=1}^k Y'_{ij}(t) dt \approx \frac{C}{T_s} \int_0^{T_s} A_1(t) e^{Z_i(t)} dt \quad (9)$$

We define $H' = \min_i Q_i$. H' can be expressed as,

$$H' = \min_i \frac{C}{T_s} \int_0^{T_s} A_1(t) e^{Z_i(t)} dt > \frac{C}{T_s} \int_0^{T_s} A_1(t) e^{-\max\{-Z_i(t)\}} dt \quad (10)$$

The inequality is due to the fact that minimum of a summation is greater than the summation of the minimum. For solving the *Minimum Power Problem* we then need to determine $\mathbb{E}[H']$ which can be written as,

$$\mathbb{E}[H'] > \frac{C}{T_s} \int_0^{T_s} A_1(t) \mathbb{E}[e^{-\max\{-Z_i(t)\}}] dt \quad (11)$$

The next step is to determine the distribution of $U = \max\{-Z_i(t)\}$. It is clear that $\{-Z_i(t)\}$ are i.i.d Gaussian random variables with mean $-\mu_z(t)$ and variance $\sigma_z^2(t)$. The maximum of i.i.d Gaussian random variables follows a Gumbel distribution asymptotically, as m the number of paths goes to ∞ with scaling factor $a_m = \frac{\sigma_z(t)}{\sqrt{2 \ln m}}$ and location factor $b_m = \sigma_z(t) \left(\sqrt{2 \ln m} - \frac{\ln \ln m + \ln(4\pi)}{2\sqrt{2 \ln m}} \right) - \mu_z(t)$ respectively [15]. Let us consider the random variable V such that $\ln V = U$. V follows a log-Gumbel distribution with the same parameters as U [15]. Therefore as $Z_i(t)$ are Gaussian, the mean of the log-Gumbel distribution exists and it follows a gamma function multiplied by an exponential.

But, we are interested in $U' = -U$ which follows a negative Gumbel distribution. Define $\ln V' = U'$. It can be easily shown that $E[V'] = e^{-b_m} \Gamma(1 + a_m)$.

$$\mathbb{E}[H'] \approx \frac{C}{T_s} \int_0^{T_s} A_1(t) \mathbb{E}[e^{U'}] dt = \frac{C}{T_s} \int_0^{T_s} A_1(t) e^{-b_m} \Gamma(1 + a_m) dt \quad (12)$$

$\mathbb{E}[H']$ computed from (12) will be an approximation to $\mathbb{E}[\min_i Q_i]$. The optimization problem thus reduces to $\min_{T_s, D} \frac{C}{T_s} \int_0^{T_s} A_1(t) e^{-b_m} \Gamma(1 + a_m) dt$, which can be easily computed numerically.

Equation (12) holds for the equal path loss scenario. But if this assumption is relaxed, the above analysis holds with minor modification until (11) - we only need to model the Gaussian variable $Z_i(t)$ to take into account the different values of C for the different links resulting from the unequal path loss assumption. If the *Minimum Power Problem* is to be solved in an unequal path loss scenario, one can obtain the distribution of $\max\{-Z_i(t)\}$ numerically (which is easy as $Z_i(t)$ are Gaussian) and then determine $\mathbb{E}[H']$. However, note that such a procedure will be computationally expensive.

VII. EVALUATION

In this section we present numerical results obtained by solving the optimization problem using (12). We first study the tradeoff between the sampling interval and the number of bits per sample for a specific set of parameters and then proceed to investigate the impact of the various parameters on this tradeoff. We consider a network of 100 nodes with

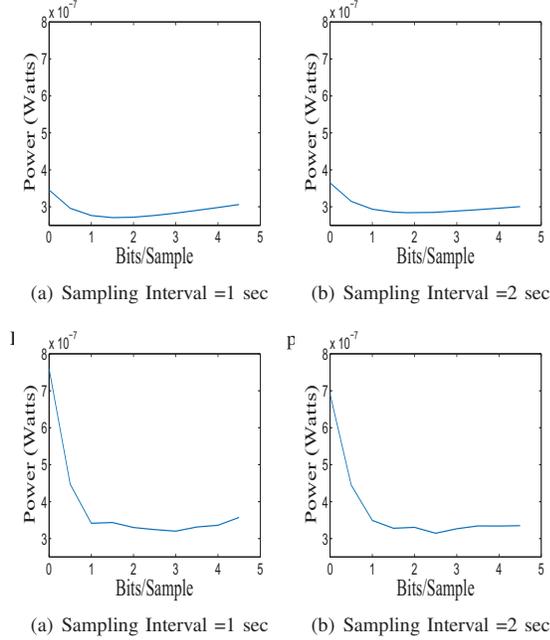


Fig. 2. Simulation: Bits per sample vs. Sampling interval tradeoff

$G = 75Kbps$, $B = 10MHz$, $S = 0.05$ and $\lambda = \frac{1}{5}$. The variance of shadowing is 25 dB. Further, we assume $m = 5$ and $k = 5$, i.e., the source has 5 disjoint paths with 5 links each. The results are obtained by increasing the number of bits per sample at a granularity of 0.5. In order to facilitate the comparison between G and C_b , we note that when $R(D) = 2$ and $T_s = 1$, $C_b \approx 10Kbps$ (Equation (3)). We also use this same configuration when we study the effect of the different parameters on the sampling interval and number of bits per sample (except for the parameter under investigation).

Figure 1 shows the variation of the transmit power with the number of bits per sample for different values of sampling interval. We observe that with a small number of bits per sample (very little information about the network), the expected power consumed is high irrespective of the length of the sampling interval. In particular, when the number of bits per sample is 0 (equivalent to choosing a path at random), the power consumed is very high. Conversely, when the number of bits per sample is high, the additional information is of marginal use in determining the minimum power path, but the overhead expended in transmitting these control bits is high.

We are interested in obtaining the global minima of the power consumed considering the entire range of the sampling interval and number of bits per sample. We observe that for the parameter values considered, the optimal value of the sampling interval is 1 second and the number of bits per sample is 1.5. Although the results in Figure 1 are obtained for $S = 0.05$, similar figures were obtained for other values of S . In the throughput range of interest (when C_t is small), the factor $(2^{C_t/SB} - 1)$ in (2) linearizes, making the power almost independent of S and vary linearly with C_t .

We have also studied the impact of the various parameters (number of nodes, shadowing correlation ($\frac{1}{\lambda}$), goodput, number of links in a path, number of paths) on the tradeoff between

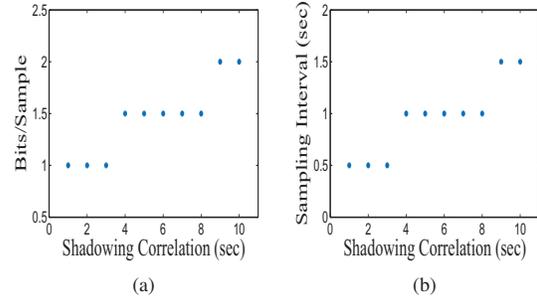


Fig. 3. Variation of Bits/Sample and Sampling Interval with Shadowing Correlation ($\frac{1}{\lambda}$)

the number of bits per sample and the sampling interval. We present few results here while the remaining are available in [15]. As these results are obtained by increasing the sampling interval and the number of bits per sample at a granularity of 0.5, the graphs are discontinuous.

We study the variation of the number of bits per sample and the sampling interval with the correlation of the shadowing process ($\frac{1}{\lambda}$) in Figures 3(a) and 3(b) respectively. Figures 3(a) and 3(b) show that both the number of bits per sample and the sampling interval increase with the shadowing correlation. This is because as shadowing correlation increases, the optimal configuration takes advantage of this by sampling at a lower frequency (longer sampling interval). Simultaneously, the number of bits per sample also increases as the decrease in overhead due to a longer sampling interval provides the network an opportunity to gather high fidelity samples.

VIII. SIMULATION

In this section we report on our use of simulations using (8) to drive the simulation, to validate our numerical results. Specifically, we study the impact of the inequality in (10) and the two main assumptions of the model - (i) approximating the sum of lognormals by a lognormal and (ii) approximating the maximum of i.i.d Gaussian random variables by a Gumbel distribution - on the accuracy of our numerical results.

We consider the same set of parameters used in the numerical evaluation. For a particular value of sampling interval and number of bits per sample, we generate shadowing measurements for all links to emulate the link state values collected at the beginning of the sampling interval. We determine the expected power consumed for the entire interval along each of the m paths and then select the path for which the expected power consumed is minimum. For each pair of values of sampling interval and number of bits per sample, we repeat this process 500 times to obtain the mean power consumed.

Simulation results depicting the tradeoff between the number of bits per sample and sampling interval with the transmit power are shown in Figure 2 and should be comparable to the numerical results in Figure 1. As in the case of our numerical evaluation, the simulation results also show that the expected power decays rapidly with an increasing number of bits per sample and then begins increasing again.

We note that the power consumption is higher in case of simulation, particularly so for a small number of bits per

sample (approaching 0). This is because our numerical analysis is an approximation that becomes better as the number of bits per sample increases. A careful examination of Figures 1 and 2 reveals that when the number of bits per sample is 0, the expected power consumed increases for numerical evaluation and decreases for simulation with increasing sampling interval. The intuitive explanation as to why the expected power decreases with an increase in the sampling interval in case of a real system (i.e., in our simulation) is the following.

Let us consider for the sake of simplicity that paths are of two types - good and bad; paths are classified as good when the power consumed at the beginning of the sampling interval is low and bad when it is high. The expected power consumed in any sampling interval is thus the additive sum of the conditional expected power consumed given a path of a specific quality (good or bad), multiplied by the probability that the selected path is of the specified quality. The above fact holds true irrespective of the duration of the sampling interval.

Let us next consider the probability of selecting a good or bad path. As shadowing is Gaussian distributed, the probability of a path being good or bad is same and is independent of the sampling interval. As the number of bits per sample is zero (equivalent to selecting a path at random), the chance of selecting good and bad paths is the same. Further, because of the exponential dependence of power on path quality, expected power expended during a sampling interval is higher when the selected path is bad in comparison to when it is good.

So far we have only considered the effect of path quality on expected power consumption. We will now reason about the impact of the sampling interval on expected power consumption. When the selected path is bad, expected power expended during a sampling interval will be higher for a shorter sampling interval than for a longer sampling interval since shadowing correlation decays exponentially. Similarly, when a good path is selected, expected power expended during the sampling interval will be lower for a shorter sampling interval.

But, the positive difference in the expected power expended between small and large sampling interval when the selected path is bad, is not compensated by the negative difference in expected power expended between them when the selected path is good. Thus, when the number of bits per sample is zero, expected power consumed when the sampling interval is small is higher than when the sampling interval is long.

Note that, although there is a mismatch between the numerical and simulation results when the number of bits per sample is small, our goal is not to study any specific scenario, but rather to determine the optimal sampling interval and the number of bits per sample. From our simulation, we find that the minimum expected power is consumed for bits per sample=2.5 and sampling interval=2 seconds, which is comparable to the numerical results (bits per sample=1.5; sampling interval=1 second). Hence we conclude that the approximations in Section VI help in modeling the system accurately. We have also studied the tradeoff between the number of bits per sample and sampling interval for a network with unequal path loss via simulation and observed that a tradeoff similar to the equal path loss case.

IX. CONCLUSION

In this paper, we formulated an optimization problem to determine the frequency at which a source should gather link state estimates and the number of bits used to encode these estimates such that the expected power consumed over a sampling interval is minimized subject to goodput constraints. We observe that long sampling intervals fail to take advantage of the temporal correlation of link state estimates while short sampling intervals incur significant overhead. Similarly, small number of bits per sample provide very little information about the network state while large number of bits provide marginal additional information. Our work can be used by network designers as a tool for determining optimal operating points (state update frequency, number of bits per sample).

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REFERENCES

- [1] J. Haerri, F. Felali, and C. Bonnet, "Performance comparison of aodv and olsr in vanets urban environments under realistic mobility patterns," in *Med-Hoc-Net*, 2006.
- [2] T. Clausen, P. Jacquet, and L. Viennot, "Comparative study of routing protocols for mobile ad-hoc networks," in *MedHoc*, 2002.
- [3] L. Viennot, P. Jacquet, and T. Clausen, "Analyzing control traffic overhead versus mobility and data traffic activity in mobile ad-hoc network protocols," *Wireless Networks*, vol. 10, no. 4, 2004.
- [4] N. Zhou, H. Wu, and A. Abouzeid, "The impact of traffic patterns on the overhead of reactive routing protocols," *IEEE Trans on Selected Areas of Comm*, vol. 23, no. 3, 2005.
- [5] N. Zhou and A. Abouzeid, "Routing in ad hoc networks: a theoretical framework with practical implications," in *IEEE Infocom*, 2005.
- [6] H. Wu and A. Abouzeid, "Cluster-based routing overhead in networks with unreliable nodes," in *IEEE WCNC*, 2004.
- [7] D. Wang and A. Abouzeid, "Link state routing overhead in mobile ad hoc networks: A rate-distortion," in *IEEE Infocom*, 2008.
- [8] V. Manfredi, M. Crovella, and J. Kurose, "Understanding stateful vs stateless communication strategies for ad hoc networks," in *ACM Mobicom*, 2011.
- [9] R. Bhatia and M. Kodialam, "On power efficient communication over multi-hop wireless networks: Joint routing, scheduling and power control," in *IEEE Infocom*, 2004.
- [10] X. Liu and A. Goldsmith, "Optimal power allocation over fading channels with stringent delay constraints," in *ICC*, 2002.
- [11] T. Rappaport, *Wireless Communications: Principles and Practice*. Prentice Hall, 2002.
- [12] M. Gudmundson, "Correlation model for shadow fading in mobile radio systems," *Electronic Letters*, vol. 27, no. 23, 1991.
- [13] J. Mazo, "Quantization noise and data transmission," *The Bell Labs Technical Journal*, 1968.
- [14] T. Cover and J. Thomas, *Elements of Information Theory*. A John Wiley and Sons, INC., Publication, 2006.
- [15] A. Seetharam, B. Jiang, D. Goeckel, R. Hancock, and J. Kurose, "Optimizing control overhead for power-aware routing in wireless networks (technical report)," <https://web.cs.umass.edu/publication/docs/2013/UM-CS-2013-022.pdf>.
- [16] P. Gupta and P. Kumar, "The capacity of wireless networks," *IEEE Trans. on Information Theory*, vol. 26, no. 02, 2000.