A Local Metric for Geographic Routing with Power Control in Wireless Networks

Chih-ping Li, Wei-jen Hsu, Bhaskar Krishnamachari, Ahmed Helmy
Department of Electrical Engineering
University of Southern California
Email: {chihpinl,weijenhs,bkrishna,helmy}@usc.edu

***Abstract*— We investigate the combination of distributed geographic routing with transmission power control for energy efficient delivery of information in multihop wireless networks. Using realistic models for wireless channel fading as well as radio modulation and encoding, we first show that the optimal power control strategy over a given link should set the transmission power to achieve a special signal-to-noise ratio (SNR) constant that can be computed using an elegant characteristic equation. Counter-intuitively, for typical radios, this corresponds to an optimal operating point of SNR that lies in the transitional region (where packet error rates are non-negligible). We then propose a local power efficiency metric for distributed routing such that at each step the transmitter picks as the next hop the neighbor for which this metric is maximized. Through extensive simulations, we compare the performance of the proposed algorithm and globally optimal routing algorithms. We show that in randomly deployed 2-D networks, the combination of this local metric for routing with optimal power control has close performances, in terms of average power consumption under different node density settings and physical transmission power limits, to the best strategy using global network link state information. In particular, when electronic power is relatively low, the proposed algorithm can provide up to six times reduction in power usage compared to channel-unaware routing algorithms.**

I. Introduction

Geographic routing protocols are of essential importance to sensor networks because they can exploit available localization information to provide low-overhead and highly scalable routing and querying. Several recent studies have stressed the importance of looking at realistic link conditions and incorporating them explicitly into the design of wireless adhoc and sensor network routing protocols [1]. In particular, as shown by Seada, Zuniga, *et al.* [2], the use of an appropriate local metric (the product of packet reception rate and distance improvement) can significantly enhance the delivery rate and energy efficiency performance of a greedy geographic forwarding.

In this paper we consider the cross-layer optimization of two key elements that significantly impact energy efficiency of delivery: (a) the selection of the appropriate link to use in forwarding a packet (i.e., the routing decision) and (b) the setting of the transmission power for transmitting a packet on that link (i.e., the power control decision). The general approach we take is to derive the optimal transmission power setting on an ARQ-enabled link that minimizes the average power needed for successful delivery. Each packet is then forwarded by a node to the next hop that maximizes a local link metric for power-efficiency, which incorporates the optimal link transmission power setting. We take into account a realistic wireless link model that incorporates both path loss and multi-path fading effects as well as radio modulation and encoding characteristics.

Thus the main focus of this paper is to examine how the energy efficiency of geographic routing can be enhanced using power control under realistic wireless conditions. Specific key contributions of this paper can be summarized as follows:

- We derive the optimal ARQ-based link transmission power setting as the one that satisfies a special SNR constant that can be very easily computed through an elegant characteristic equation.
- We show that, somewhat counter-intuitively, the optimal SNR constant typically corresponds to an optimal packet reception rate at the receiver that is high, but not arbitrarily close to 100%.
- We show that, particularly when electronic power costs are low, combining routing with power control can provide up to six times savings in energy compared to fixed power routing.
- We propose a new local metric for geographic routing: the ratio of the product of the packet reception rate and distance improvement to the total power expense for a single packet transmission.
- We show that distributed geographic routing using this local metric can provide close performance compared to the best routing strategy that utilizes global link-state information.

One important assumption made in this paper is that, to be able to utilize channel conditions for performance improvement, we focus on networks with relatively stable wireless channels. It is a practical assumption when a wireless network is in an isolated remote environment with either slow-moving or no mobility events. When a sending node tries to measure channel parameters, such as multi-path fading factor or noise level, to its neighboring nodes, we assume these channel parameters remain unchanged for time periods longer than the typical packet transmission time. We assume these channel parameters are obtainable by exchanging control messages or overhearing [5] [6].

The rest of the paper is organized as follows: Section II gives a review of research literature related to routing

0-7803-9011-3/05/$20.00 ©2005 IEEE.

and power control mechanisms in wireless networks. The framework of the network model is introduced in Section III. Optimal power control for single-hop reliable transmissions is defined and analyzed in Section IV. In Section V, the joint distributed routing and power control mechanism as well as the corresponding local metric for routing is proposed. The optimal-static route in linear networks, as a baseline scenario compared with our proposed algorithm, is analyzed as well. Extensive simulations on both linear networks and general 2-D networks are given in Section VI. Section VII presents our concluding comments.

II. Related Work

Recent experimental research has revealed how drastically link conditions in realistic wireless networks vary from the ideal disk model [3]–[6]. In particular, Zhao and Govindan [4] and Woo et al. [5] identified the existence of a gray area/transitional region that is characterized by high link quality variance and asymmetric links. Zuniga and Krishnamachari [7] provide an analysis of this transitional region using a log-normal multi-path fading model. Our work is motivated by this line of research which has also made it clear that is essential to incorporate the realistic link models into the design and evaluation of routing protocols [1]. DeCouto *et al.* [6] and Woo *et al.* [5] independently proposed the ETX/MET metric which tries to find a route such that the total expected number of retransmissions due to packet drops is minimized.

Geographic routing protocols (see survey in [9]) are of essential importance to wireless sensor networks. They make use of available localization information, and can provide a significant reduction of complexity and overhead. While there has been prior research on preventing dead-ends in geographic routing through face-routing techniques (e.g. [8]), we assume in this work that the density is sufficiently high that greedy geographic forwarding is sufficient to ensure end-to-end delivery. Based on the realistic channel modeling, Seada, Zuniga, *et al.* [2] look into the issue of power-aware greedy geographic forwarding. That work assumes a fixed transmission power and focuses on mechanisms for making routing decisions based on channel estimations in static environments. In this paper, we take a crucial step further to incorporate transmission power control. As we shall show, this can provide great savings in energy.

While there is extensive prior work on power control, most of it focuses on topology control, the main purpose of which is to reduce interference and enhance spatial reuse. Kleinrock [20] identifies the optimal transmission radius to maximize network capacity in multi-access networks. Takagi and Kleinrock [21] find the optimal transmission radii to maximize the packet forward progress in several multi-access schemes. Hou and Li [22] present a model showing that throughput and forward progress can be improved by adjusting transmission power. Other papers provide desirable global connectivity properties with low energy utilization (e.g. [10], [11], [23]).

Different from the earlier approach, in this paper our main goal is to emphasize the necessity to consider a more realistic communication model, and design a joint power control and routing scheme from that point of view. Power control in this paper aims to achieve energy efficiency rather than improve throughput. Therefore our model is more suitable for networks with stringent energy constraint but low data rates, such as sensor networks. Here we assume the interference is resolved by some MAC sleep/wakeup scheduling schemes (e.g., [24]), which are orthogonal to this work and can be used in conjunction with our algorithm to reduce the overall energy and extend network lifetime.

There has also been some work examining the combination of power control with routing (e.g. [12], [13]). However, nearly all of these works assume an idealized wireless channel model unlike our work. Son et al. [14] do present an extensive experimental analysis of power control and propose a technique for combining it with black listing to provide reliable routing. However, they do not address the issue of cross-layer optimization for energy efficiency.

Another approach to energy efficiency in wireless sensor network routing is to develop power-aware metrics that take into account residual battery levels in order to extend network lifetimes by providing load balancing [15], [16]. The technique we propose in this work may be combined with power-aware metrics for load-balanced maximum lifetime routing.

While we use sophisticated models for wireless environments and radio characteristics, we should note one real-world effect that is not incorporated explicitly in our work. We assume, as in standard communication theory, that there is a perfect one-to-one, monotone mapping from SNR to packet reception rate depending on the modulation scheme. A recent experimental study [17] shows that in practice this mapping can show high variance depending on the node hardware. However, our approach can be modified to take this into account either by pre-characterizing the curve for each pair of transmit-receiver nodes or by using a more conservative setting of higher transmission power than needed as per the derived expression.

III. Formulation of Network Models

A. Energy Model

The goal of power control is to find the minimum power needed for internal operations and communications of wireless devices. To characterize it, first we define the energy model. We define the power consumption of a wireless device is the sum of transmission and electronic power. Electronic power is the power needed for on-board circuits to operate when preparing for packet transmissions. Note that the reception power is practically not negligible because it is generally of the same order as the transmission power. In this paper, we assume either all nodes are always listening to potential packet receptions, or there are some sleep scheduling algorithms operating such that all nodes start listening to receiving channels only when necessary. In the former case, the reception power dissipation is constant; in the latter case, reception power can be viewed as proportional to the transmission power. Therefore minimizing transmission power is equivalent to minimizing the sum of transmission and reception power. This proportionality between the transmission and reception power holds when we consider the aggregation of power expenditure of all nodes in the network; it may not hold for any particular node.

B. Channel, Modulation, and Encoding Model

The joint power control and routing scheme proposed in this paper depends on the relationship between transmission power and packet reception rate, which are modeled by channel, modulation, and encoding schemes in physical layer. We specify these models as following: When electromagnetic signals propagate via wireless links, their strength will suffer from decays. Moreover, they also exhibit spatial and temporal variations. To model this phenomenon, we use one of the most common models — *log-normal multi-path fading model* [18]:

$$PL(d)^{dB} = PL(\hat{d})^{dB} + 10\ \gamma\ log_{10}(\frac{d}{\hat{d}}) + X_\sigma^{dB} \tag{1}$$

Where $PL(d)^{dB}$ is the power loss after the signal propagates through distance d, $PL(\hat{d})^{dB}$ is the power loss at the reference distance $\hat{d}$, γ is the path loss exponent, and X_σ^{dB}, a Gaussian random variable with mean zero and variance σ^2, models the multi-path fading effect between a transmitter-receiver pair [1]. Then the reception power P_{recv}^{dB} is equal to the transmitting power P_{trans}^{dB} minus the path loss $PL(d)^{dB}$: $P_{recv}^{dB} = P_{trans}^{dB} - PL(d)^{dB}$. The Signal-to-Noise Ratio (SNR) at the receiver end is:

$$SNR^{dB} = P_{recv}^{dB} - N^{dB} \tag{2}$$

Modulation is a mapping from SNR to bit error rate. In order to facilitate the analysis and bring insight on good power control and routing mechanisms, we take non-coherent FSK [19] as an example throughout the paper, due to its simple mathematical form. For non-coherent FSK, the bit error rate is given by:

$$P_e = \frac{1}{2}\exp^{-\frac{1}{2}SNR} \tag{3}$$

Encoding schemes influence packet reception rate because they add redundant error correction bits to a packet. In this paper, we use NRZ encoding in our modeling. We define F (with unit of bytes) to be the size of a packet after being encoded by NRZ. We assume bit errors occur independently. The packet reception rate prr is:

$$prr = (1 - P_e)^{8F} = (1 - \frac{1}{2}\exp^{-\frac{1}{2}SNR})^{8F} \tag{4}$$

IV. Optimal Power Control for Single-Hop Reliable Transmission

One of the characteristics of wireless communications is the high bit error rate compared to traditional wired networks. Packets are corrupted and retransmitted more often in wireless environments. Naturally power control should accommodate this concern. As a result the optimum transmission power on a given link should be the minimum power needed for a *successful* transmission, which may include multiple retransmissions. With ARQ, number of transmissions needed for a successful one can be modeled as a geometric random variable. In this paper, we characterize the optimal power consumption for reliable transmissions by the minimum *average* power needed on either a given link or an end-to-end path between a source-sink pair, i.e., the long-term behavior of power dissipation over a wireless channel or a specific route. And we define the *optimal transmission power* to be the minimum expected transmission power needed for reliable information delivery in wireless networks.

The channel, modulation, and encoding model given in the previous section relate the transmission power to the packet reception rate. Assume bit error occurs inpedendently, and a packet is retransmitted according to some timeout or ARQ scheme if it fails in its previous attempt. Assume the cost of the timeout or ARQ scheme is negligible. Then the expected power to reliably transmit a packet on a given link is:

$$\frac{P_{trans} + P_{elec}}{prr} = \frac{10^{\frac{P_{trans}^{dB}}{10}} + P_{elec}}{(1 - \frac{1}{2}\exp^{-\frac{1}{2}SNR})^{8F}} \tag{5}$$

Where P_{trans} and P_{elec} are transmission and electronic power for a single transmission, respectively. The prr is derived according to non-coherent FSK modulation and NRZ encoding scheme. By (2),

$$\begin{aligned} SNR^{dB} &= P_{trans}^{dB} - PL(d)^{dB} - N^{dB} && (6)\\ &= P_{trans}^{dB} - 10\gamma\log_{10} d - X_\sigma^{dB} - N^{dB} && (7)\\ &\quad -(PL(\hat{d}) - 10\gamma\log_{10}\hat{d}) \end{aligned}$$

Change the unit from dB to Watt [2]:

$$SNR = SNR(P_{trans}^{dB}) = \frac{10^{P_{trans}^{dB}/10}}{CX_\sigma N}\ d^{-\gamma} \tag{8}$$

Where the constant $C \triangleq 10^{(PL(\hat{d}) - 10\gamma\log\hat{d})/10}$. Minimizing (5) over P_{trans}^{dB} gives us the optimum power consumption for reliable transmissions over a single link. To think of it in another way, we note that minimizing (5) is equivalent to maximizing its reciprocal:

$$\begin{aligned} g(P_{trans}^{dB}) &\triangleq \frac{prr}{P_{trans} + P_{elec}} && (9)\\ &= \frac{(1 - \frac{1}{2}\exp^{-\frac{1}{2}SNR})^{8F}}{10^{\frac{P_{trans}^{dB}}{10}} + P_{elec}} && (10) \end{aligned}$$

The physical meaning of the reciprocal function $g(P_{trans}^{dB})$ is the expected number of packets that can be successfully transmitted by spending one unit of power. In other words, it provides an indication of *power efficiency*, i.e., minimizing the required power for reliable transmissions is equivalent to maximizing the power efficiency. To maximize (10), expand the numerator of (10) using binomial theorem, take a derivative

[1]Many variables used in this paper are referred with both units of dB and Watt. For clarification, we put a superscript *dB* on a variable if its unit is dB; a power variable without superscript dB is in Watts.

[2]$SNR \triangleq 10^{SNR^{dB}/10}$, $X_\sigma \triangleq 10^{X_\sigma^{dB}/10}$, and $N \triangleq 10^{N^{dB}/10}$

of $g(\cdot)$ with respect to P_{trans}^{dB}, and set the derivative to zero we get the following characteristic equation:

$$\frac{A}{2} - 4FA\ln(A) + \frac{2FA}{CX_\sigma Nd^\gamma}P_{elec} = 1 \qquad (11)$$

Where $A \triangleq \exp^{-\frac{1}{2}SNR}$ (since $SNR \geq 0$, $A \in [0,1]$), and F is the size of a packet. Let the set Λ be the collection of all solutions to (11). By optimization theory, the optimal point A^* maximizing the function $g(P_{trans}^{dB})$ must lie in the union of the set Λ and boundary points of A. A^* can be easily calculated by numerical approaches ((11) is transcendental and may not have closed form solutions). Note that if the electronic power is negligible, the optimal point A^* only depends on the packet size. Therefore given the packet size, the optimal A^* is a fixed special value. It implies that there exists a power-efficient operating point of SNR which we always want to achieve by allocating a certain level of transmission power, no matter how the values of inter-node distance d, log-normal multi-path fading factor X_σ, and thermal noise N would change spatially and temporally. It results in an optimal power allocation policy:

> ***fixed-SNR policy for optimal power control***:
> Define the optimal power to be the minimum expected power for reliable transmissions. Assume electronic power dissipation is negligible. Let a transmitter-receiver pair, the corresponding inter-node distance, and modulation and encoding scheme be all given. After the measurement or prediction of X_σ and N of the wireless channel between the transmitter and the receiver, allocation of transmission power to satisfy the desired $snr^* = -2\ln(A^*)$ can minimize the required power of reliable packet relay.

According to this policy, the optimal SNR snr^* is fixed. Then the optimal bit error rate P_e^* and the optimal packet reception rate prr^* are also fixed. Finally, by (8), the optimal transmission power of one transmission attempt for a transmitter-receiver pair with inter-node distance d is given as:

$$P_{trans}^* = C\ snr^*\ X_\sigma\ N\ d^\gamma \qquad (12)$$

The optimal transmission power for reliable transmissions is:

$$\frac{P_{trans}^*}{prr^*} = \frac{C\ snr^*\ X_\sigma\ N}{prr^*}d^\gamma \qquad (13)$$

To give an example, let $P_{elec} = 0$, $F = 100$. By solving (11), the optimum A^* is 0.00031, $SNR^* \approx 16.16$, $P_e^* = A/2 = 0.000155$, and $prr^* = (1 - P_e^*)^{800} \approx 0.8838$. Therefore to achieve the optimal power consumption, we should allocate the transmission power to satisfy $SNR = 16.16$. The packet reception rate would be 0.8838, a number is high but not close to one. It implies that once the fixed-SNR policy is obeyed, transmitting packets leading to the 0.8838 throughput at every hop is most power-efficient. It also implies the most power-efficient operating point of SNR should lie within the *transitional region* [7]. It suggests the need to incorporate transitional region modeling when designing future power-aware network protocols.

By (11), if electronic power is not negligible, the SNR leading to the most power-efficient packet delivery is a function of channel conditions, distance to the next hop, electronic power, and the packet size. If we consider a stable network environment with no mobility events, the channel parameters and distance to the next hop are considered relatively constant. In this case, for a transmitting node of which the electronic power is known from hardware specification, the fixed-SNR policy for optimal power control still holds. But each transmitter-receiver pair will have different optimal SNR value.

Earlier we assume the transmission power can be arbitrarily chosen to meet the optimal SNR level. Practically, a physical limitation of transmission power should be considered. In this case, when trying to maximize the power efficiency function $g(P_{trans}^{dB})$, the additional limitation can be easily met by putting an constraint on the range of A. The rest of the derivations and conclusions remain the same. Finally, the characteristic equation (11) is specific to non-coherent FSK modulation and NRZ encoding schemes. In general, the characteristic equation of SNR depends on different modulation and encoding scheme. Since the only property of the $SNR - P_e$ mapping used to derive the characteristic equation is differentiability, our framework is applicable to various modulation schemes as long as the $SNR - P_e$ relationship satisfies differentiability.

V. Local Metric for Distributed Routing with Power Control

The previous section analyzes the optimum power needed for reliable transmissions on a wireless link. For end-to-end transmissions over multihop wireless networks, however, an efficient transmission strategy not only includes optimal power control, but also chooses a route with good channel conditions. Therefore we explore an efficient joint power control and routing strategy for end-to-end communications.

There are several assumptions of the network model made here. First we assume the wireless network of interest is relatively stable. When the state of a channel changes with time, it changes in an identical and independently distributed (i.i.d.) fashion; and channel conditions of all wireless links at any time instant are assumed i.i.d.. The channel parameters related to our work are multi-path shadowing factor X_σ and thermal noise N. Since they have no obvious correlation with the general network setup, it is reasonable to make i.i.d. assumptions. Second, we assume every node knows its own and all its neighbors' geographical locations, by either GPS services or cooperative ranging techniques. Third, we assume no interference is experienced by all packet transmissions.

A. Local Metric

We define a novel local metric for the proposed algorithm: Let a transmitter-receiver pair with inter-node distance d be given. Assume the link parameters between the pair, such as the multi-path fading factor X_σ and thermal noise at the

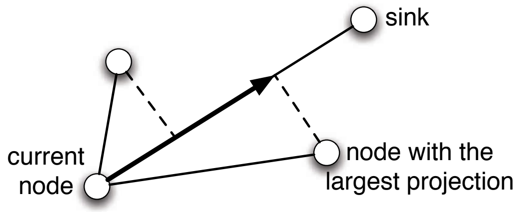

Fig. 1. Projection of the hop distance onto the line toward the sink node

receiver end N, are known in advance by measurements. According to Section III-B, the SNR and packet reception rate can then be calculated. From Section IV, the minimum expected power required can be calculated as well. We define a local metric:

$$metric \triangleq \frac{prr^* \cdot D_{proj}}{P^*_{trans} + P_{elec}} \tag{14}$$

By (12) P^*_{trans} is the optimal transmission power for one transmission attempt, prr^* is the optimal packet reception rate, and D_{proj} is the virtual distance progress toward the sink node — the length of the projection of the distance vector between the transmitter and the next hop onto the line formed by the transmitter and the sink (see Figure 1). In linear networks, D_{proj} reduces to the distance between the transmitter and the next hop. The local metric has a practical meaning: It is the *maximum expected transport capacity* per unit power consumption, an indication of power efficiency. The corresponding power control and routing strategy is:

Joint Distributed Routing and Power Control (JDRPC): for each transmitting node, choose one of its neighbors such that the local metric given in (14) is maximized. Then transmit packets according to the fixed-SNR policy.

B. Optimal-Dynamic and Optimal-Static Routes

In order to analyze the performance of the algorithm, we compare it with the globally optimal routing mechanisms. First note that if channel conditions in a wireless network change rapidly, it is impossible to find an optimal route between any source-sink pair even with global knowledge of link state information. It is because the *best* route found at the beginning of a transmission is potentially no longer the best one when the packet is along the way to the receiver. Therefore in order to have well-defined notions of *global-optimal route*, here and later in the simulation section, we assume channel conditions remain fixed for the time duration of the end-to-end transmission of one packet.

We consider two types of global-optimal routes in wireless networks. One is the optimal-dynamic route, i.e., routes for different packets can be different according to time-varying link state information. The optimal-dynamic route for each packet can be found by performing shortest-path mechanisms, such as Dijkstra algorithm. Combining it with optimal power control on every wireless link, it is easy to find the path with minimum expected power consumption for the end-to-end communication of a single packet. Note that here we assume the problem of joint routing and optimal power control can be separated, but still yield the optimal solution. It is a reasonable assumption because we assume there is some MAC layer scheduling mechanism taking care of interference issue; therefore power consumption is independent among all hop-by-hop transmissions. The optimal power of a route is the sum of optimal power of all links along the route. Then finding the route with the least total power is equivalent to finding the shortest path where the metric is the optimal power on every link.

The other type of global-optimal route is optimal-static route, where we focus on the long-term behavior of routes in wireless networks. In this case, we compare the performance of two different routes in wireless networks by their minimum expected power consumption averaged over random link states; i.e., the time average of minimum expected power consumption by transmitting a sequence of packets, that may experience different wireless channel states along the same route. We emphasize that there are two notions of *average power*: expected power on a given link is due to imperfect packet receptions and retransmissions, while time average of expected power over a channel is due to time-varying channels. If not comparing the performance of wireless routes by their long-term behaviors, we will need a more refined probabilistic model for channel states. Developing probabilistic arguments for performance comparison of different routes will be both too complicated and indefinite. As a result, we define the *optimal-static route* between any source-sink pair to be the route with minimum time average (over channel states) of expected (consider packet retransmissions) power consumption.

The optimal-dynamic route we consider in this paper is constructed by Dijkstra algorithm. The optimal-static route, however, depends on different electronic power setup and particular network topology. To reveal this issue, in the following we derive the optimal-static route in a linear work as a function of electronic power settings, considering all possible node deployment strategies.

C. Derivation of Optimal-Static Route

We consider a general linear network with N nodes $\{n_1, n_2, n_3, \ldots, n_s, \ldots, n_d, \ldots, n_N\}$ located sequentially on a line with arbitrary inter-node distances (see Figure 2). N can be any integer greater than two. Let $d_i > 0$ be the inter-node distance between node n_i and n_{i+1}, $i \in \{1, 2, 3, \ldots, N-1\}$. Without loss of generality, assume n_s is the source node of interest, and n_d is the intended destination node, $s < d$. All other nodes potentially help to relay packets from n_s to n_d. For simplicity, define the distance between n_s and n_d to be D_{sd}. To take all possible static routing strategies into account, we assume each node is able to transmit packets directly to any other nodes in the network. Let $\{X_{i,j}(t)\}$ represent the random process of multi-path fading factor for link between node n_i and n_j, $i, j \in \{1, 2, 3, \ldots, N\}, i \neq j$. For any given t, $\{X_{i,j}(t)\}$ is i.i.d. for all possible $(n_i,\ n_j)$ pairs; for any

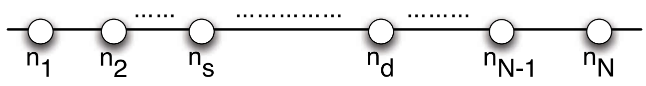

Fig. 2. The linear network

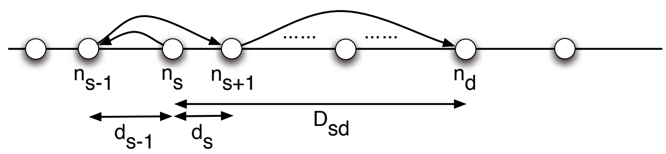

Fig. 3. An example of route

(n_i, n_j) pair, $\{X_{i,j}(t)\}$ is i.i.d. for all t. Assume $\{N_i(t)\}$ is the noise process observed at any node n_i. Similarly, $\{N_i(t)\}$ is i.i.d. for all nodes at some time instant t and for all time instants at some node n_i.

Consider the pair of nodes (n_i, n_{i+1}) with inter-distance d_i, multi-path fading factor $X_{i,i+1}$, and thermal noise N_{i+1} at the node n_{i+1}. By (8), the optimal transmission power from n_i to n_{i+1} is:

$$\frac{P^*_{trans}}{prr^*} = \frac{C\ snr^*}{prr^*} X_{i,i+1}\ N_{i+1}\ d_i^\gamma \tag{15}$$

Where P^*_{trans} is the optimal transmission power for a transmission attempt from node n_i to n_{i+1}, snr^* is the optimal SNR according to the *fixed-SNR policy*, and prr^* is the corresponding optimal packet reception rate.

Theorem 1: The best route, minimizing the average end-to-end power consumption, between a source-sink pair with distance D and electronic power P_{elec} in linear networks is hop-by-hop routing strictly toward the receiver, where all hops traverse the same distance d with

$$d = \min\{D, \sqrt[\gamma]{\frac{P_{elec}}{(\gamma-1)C\ snr^*\mathbb{E}[XN]}}\} \tag{16}$$

Proof: Every route between n_s and n_d can be represented as a *walk* along the line. We define a sequence $\{a_m\}_{m=1}^\infty \in \mathbb{R}^\infty$, $\sum_{i=1}^\infty a_i = D_{sd}$ to represent the sequence of steps in a walk, where a_m is the m_{th} step of the walk, $a_m > 0$ and $a_m < 0$ mean that the m_{th} step goes forwards and backwards, respectively; and $|a_m|$ is the distance traversed by the m_{th} step, which must be the distance between some pair of nodes. For example, the sequence of steps $\{-d_{s-1}, d_{s-1}+d_s, D_{sd}-d_s, 0, 0, 0, \ldots, 0\}$ represents the route $n_s \rightarrow n_{s-1} \rightarrow n_{s+1} \rightarrow n_d$ (see Figure 3). Given some $M > 0, M \in \mathbb{N}$. Consider a walk $\{a_m\}_{m=1}^M \in \mathbb{R}^M, \sum_{i=1}^M a_i = D_{sd}$ representing a route strictly using M hops between the source n_s and the sink n_d with inter-node distance D_{sd}. The time average of optimal power consumption of the walk is (15):

$$M\ \frac{P_{elec}}{prr*} + \frac{C\ snr^*\mathbb{E}[XN]}{prr^*} \sum_{m=1}^M |a_m|^\gamma \tag{17}$$

By applying Hölder inequality, the summation of the second term in (17) can be lower bounded by:

$$D_{sd} = |\sum_{m=1}^M a_m| \le \sum_{m=1}^M |a_m| \le (\sum_{m=1}^M |a_m|^\gamma)^{\frac{1}{\gamma}}\ M^{1-\frac{1}{\gamma}} \tag{18}$$

$$\frac{D_{sd}^\gamma}{M^{\gamma-1}} \le \sum_{m=1}^M |a_m|^\gamma \tag{19}$$

The lower bound is achieved when $a_1 = a_2 = \ldots = a_M = D_{sd}/M$, i.e., the minimum time average of optimal power consumption is achieved when all M hops traverse the same distance toward the sink node.

From above we know that the best node deployment policy in the linear network is to place nodes uniformly between the source-sink pair; and the optimal route is hop-by-hop forwarding from the source to the sink. The time average of end-to-end power consumption can be minimized over the number of nodes to be put between the source-sink pair. Take a derivative of (17) after substituting $a_1 = a_2 = \ldots = a_M = D_{sd}/M$ and set it to zero, the optimal M is:

$$M^* = D \sqrt[\gamma]{\frac{(\gamma-1)C\ snr^*\mathbb{E}[XN]}{P_{elec}}} \tag{20}$$

The optimal advance for each hop is then $d^* = D/M^*$. Since the maximal possible value of d^* is D, we have:

$$d^* = \min\{D, \sqrt[\gamma]{\frac{P_{elec}}{(\gamma-1)C\ snr^*\mathbb{E}[XN]}}\} \tag{21}$$

■

Given a typical range of P_{elec}, it is interesting that the optimal distance a hop should traverse is a function of electronic power — the larger the electronic power is, more preferable it is to go longer hops — but independent of the distance between the source and the sink node. Furthermore, the optimal number of hops M^* in (20) may not be an integer. Practically, the optimal number should be either $\lceil M^* \rceil$ or $\lfloor M^* \rfloor$. Since we have considered all possible walks for the optimal route, including those walks with backward transmissions, we don't make any assumptions regarding what the best static route should be.

VI. Performance Evaluation of JDRPC Algorithm

We evaluate the performance of JDRPC algorithm through extensive Monte-Carlo simulations. We compare JDRPC with static hop-by-hop routing, optimal-static routing, and optimal-dynamic routing in linear networks. In 2-D networks, we compare JDRPC algorithm with the optimal-dynamic routing and two less intelligent routing algorithms: Fixed-transmission-power routing and Distance-based routing. In this paper, we use Dijkstra algorithm to implement the optimal-dynamic routing.

A. Simulations on Linear Networks

Consider a linear network with 21 nodes $\{n_1, n_2, \ldots, n_{20}, n_{21}\}$. Let node n_1 be the source node generating packets destined for the sink node n_{21}. We fix the distance between the source and sink to be 200 meters. The other 19 nodes are deployed between the source-sink pair; inter-node distances are specified later. We assume all nodes are able to adjust transmission power arbitrarily. Thus all nodes can send packets directly to any other node, and allocate optimal transmission power according to (12) for all possible link state information. Both transmission and electronic power are considered in the simulations. As mentioned in Section IV, we assume channel conditions remain fixed during the time period of the end-to-end transmission of every packet. The strict assumption is needed only for the optical dynamic route (derived by Dijkstra algorithm) to exist. But to be comparable, the same channel assumption is applied to all routing schemes. We note that JDRPC does not need such a stringent channel setup; it works equally well as long as the local channel information, potentially time-varying, can be correctly captured (this part of simulation is omitted for brevity). When channel states change, the multi-path fading factor $\{X_{i,j}(t)\}$ is i.i.d. with respect to t and different channels (i, j); the thermal noise process $\{N_i(t)\}$ is i.i.d. with respect to t and different locations n_i.

We consider two types of network topologies: random and uniform node deployment, where intermediate nodes are deployed randomly and uniformly between the source-sink pair, respectively. In the randomized linear network, we compare three routing strategies: Dijkstra, JDRPC, and hop-by-hop static routing. The Dijkstra algorithm utilizes global knowledge of channel state information to find the shortest end-to-end path in terms of minimal expected power for reliable transmissions. It is used as a baseline to show how good JDRPC can be compared to the shortest path (in the expected sense). JDRPC algorithm is well illustrated in Section V-A. Again, this strategy is *greedy* in the sense that a node picks its next hop, only based on local knowledge of all outgoing channels, to maximize the transport capacity toward the sink node per unit power. In hop-by-hop routing, a node always transmits packets with optimal transmission power control to the nearest neighbor toward the sink. Since by Theorem 1, the optimal-static route is of uniform node deployment, we do not consider it in randomized linear networks. We consider all three routing strategies in the simulations on uniform-deployed linear networks.

The simulation is repeated for 10000 iterations for each routing strategy on each of the two topologies. For each iteration, we pick i.i.d. realizations of $X_{i,j}$ and N_i — $X_{i,j}$ is a normal random variable with mean 0 dB and variance 6.0 dB^2, and N_i is Gaussian with mean -135 dB and variance 10 dB^2. Non-coherent FSK modulation and NRZ encoding are utilized. The path loss exponent is set to be 4.0. The encoded packet size is fixed to be 100 bytes. Node locations are re-assigned in each iteration for randomized linear networks.

TABLE I

COMPARISON OF ROUTING SCHEMES IN LINEAR NETWORKS

(a) Metrics for random deployment

P_{elec}	routing scheme	avg. end-to-end power	average step size
10^{-1}	Dijkstra	1.332	2.64
	JDRPC	1.590	2.67
	Hop-by-hop	2.812	1.0
10^{-3}	Dijkstra	0.374	1.38
	JDRPC	0.495	1.39
	Hop-by-hop	0.662	1.0
10^{-5}	Dijkstra	0.370	1.22
	JDRPC	0.488	1.20
	Hop-by-hop	0.659	1.0

(b) Metrics for uniform deployment

P_{elec}	routing scheme	avg. end-to-end power	average step size
10^{-1}	Dijkstra	1.172	2.52
	JDRPC	1.351	2.52
	Optimal static (10hops)	1.4655	2.0
	Hop-by-hop	2.207	1.0
10^{-3}	Dijkstra	0.068	1.06
	JDRPC	0.072	1.07
	Optimal static (hop-by-hop)	0.071	1.0
10^{-5}	Dijkstra	0.047	1.05
	JDRPC	0.048	1.06
	optimal static (hop-by-hop)	0.047	1.0

We also evaluate the performance of all routing strategies under three different electronic power settings: 10^{-1}, 10^{-3}, and 10^{-5} Watts, corresponding to extremely large to negligible electronic power.

B. Simulation Results for Linear Networks

Table I shows the average end-to-end power consumption and average *step size* for all routing strategies in different electronic power settings and different network topologies. We define *step size* as follows: We index the nodes on the line in increasing order from the source to the sink, with the source being 1 and the sink being 21. *Step size* of a hop is defined as the difference between the indices of nodes on both ends of the hop. Note that the average end-to-end power presented in the tables are *exact* values, taking exact power expenditure on retransmissions into account, not expected ones as derived in the previous anlysis.

First we compare the average end-to-end power consumption between Dijkstra and JDRPC algorithms in both network topologies. For all electronic power settings, although JDRPC is only based on local link state information, its average power consumption is close to that of Dijkstra algorithm. In the worst case, JDRPC uses about 30% of average power more than Dijkstra algorithm when nodes are randomly deployed. When the electronic power is low and nodes are uniformly deployed, the performance of JDRPC is very close to that of Dijkstra algorithm, the globally optimal one. Therefore JDRPC should be a good candidate of distributed power-aware routing algorithm in wireless networks.

Second, in both network topologies, we observe that as the electronic power increases, the average step size of JDRPC algorithm increases. It shows that JDRPC algorithm can adapt to different electronic power settings by traversing appropriate distance in each hop. On the contrary, the step size of hop-by-hop routing is fixed to one. Therefore its performance degrades serevely at high P_{elec} setting.

In the uniform-deployed network, we put optimal-static routing into the comparison. By Equation (21), the distance of one hop on the optimal-static route increases with electronic power. In the simulation for $P_{elec} = 10^{-5}$ and 10^{-3} Watt, the optimal inter-node distance is so small that the optimal-static routing reduces to hop-by-hop forwarding. For $P_{elec} = 10^{-1}$ Watt, by the discussion at the end of Section V-C, the optimal-static route is to go 10 hops uniformly from the source to the sink.

In general, when the electronic power is high (10^{-1} Watt), JDRPC and Dijkstra algorithm perform better than the optimal-static route because the former two algorithms are able to pick a route with better channel conditions; the optimal-static route always follows the same route. When the electronic power is negligible, JDRPC and Dijkstra algorithm give little improvement because they prefer shorter hops as the optimal-static route does. Note that the optimal-static route performs no worse than hop-by-hop routing due to its capability to choose a longer hop, especially when the electronic power is high.

Third, consider the average power consumption for hop-by-hop routing in both network topologies. For all electronic power settings, the average power consumption in the uniform-deployed network is less than that of the randomized network, consistent with the conclusion in Theorem 1 that uniform forwarding is more preferable. The difference is particularly pronounced for the scenario of low P_{elec}, in which transmission power dominates the total power consumption.

C. Simulations on 2-D networks

For 2-D scenario, we consider 100 nodes randomly deployed in a square area of size 100×100 meter square. The source and the sink node are fixed at two corners across the diagonal of the square area. The setup for energy, channel, modulation, and encoding model is the same as those in the linear network. All simulations on 2-D networks are run for 10000 iterations. For each iteration, node locations are randomly re-assigned; X_σ for all links and N for all nodes are re-assigned in an i.i.d. fashion.

We compare four different routing strategies: Dijkstra, JDRPC, *Fixed-transmission-power* routing, and *Distance-based* routing. Dijkstra and JDRPC algorithm are illustrated in Section V-A. The Fixed-transmission-power routing allows a sending node to choose the next hop in its local neighborhood within the radius R to make the maximal progress toward the sink. In simulations R is set to be 20 meters. Then it allocates the fixed transmission power P_T to each packet. P_T is set to be the optimal transmission power for a receiving node R distance away with $X = \mathbb{E}[X]$ and $N = \mathbb{E}[N]$ because a transmitter tries to locate the next hop as near its transmission boundary toward the sink as possible. Simulating on this routing strategy is meant to emphasize the importance of having a *power control* mechanism along with routing in wireless networks.

In Distance-based routing, we assume nodes are oblivious of channel conditions. It finds the best end-to-end path with the least expected end-to-end power consumption, utilizing only the distance information between nodes. In (12), the transmission power allocated on a link is P^*_{trans} with $X = \mathbb{E}[X]$ and $N = \mathbb{E}[N]$, equivalent to using d^γ as the link metric. It demonstrates the inefficacy of allocating transmission power based only on topological information. The inefficacy is because time-varying channel conditions are not utilized in making routing and power control decisions.

Fixed-transmission-power and Distance-based routing may choose a link with extremely low packet reception rate due to poor transmission power control decisions as they are unaware of channel conditions. As a result, in the simulation we set a *retransmission threshold* such that if packet retransmissions fail on the same link consecutively for 30 times, the sender will give up sending packets on the link and this iteration is considered as a failed trial. For Dijkstra and JDRPC algorithm, since transmission power is arbitrarily adjustable to achieve the optimal packet reception rate for all possible link conditions, successive transmission failures are not observed.

TABLE II

COMPARISON OF ROUTING SCHEMES IN RANDOMIZED 2-D NETWORKS

(a) Average end-to-end power (Watt)

P_{elec}	Dijkstra	JDRPC	Fixed power	Distance-based
10^{-1}	0.7360	0.8363	1.7772	1.8670
10^{-3}	0.0505	0.0726	0.3886	0.1108
10^{-5}	0.0306	0.0557	0.3677	0.0900

(b) Average hop count on end-to-end path

P_{elec}	Dijkstra	JDRPC	Fixed power	Distance-based
10^{-1}	5.01	5.39	9.85	7.00
10^{-3}	15.98	14.31	9.86	18.56
10^{-5}	22.97	18.50	9.82	23.67

(c) Successful transmissions out of $10,000$ trials

P_{elec}	Dijkstra	JDRPC	Fixed-power	Distance-based
10^{-1}	10,000	10,000	3,223	1,631
10^{-3}	10,000	10,000	2,496	48
10^{-5}	10,000	10,000	2,231	3

D. Simulation Result for 2-D Networks

1) Performance: Table II shows the average end-to-end power consumption, average hop count, and the number of successful end-to-end transmissions (out of 10000) for the four routing schemes. First, for average power consumption, JDRPC algorithm, which is only based on local link state information, performs close to Dijkstra algorithm for all electronic power settings. In addition, the advantage of JDRPC over Dijkstra is that it only requires channel information to one-hop neighbors. This information can be collected much faster and more accurate compared to the global information needed for Dijkstra algorithm. The ovevheard of computation and communication is also reduced, making JDRPC a good power control and routing algorithm. Fixed-transmission-power strategy incurs much larger power consumption compared to the former two schemes, due to its incapability to adapt to

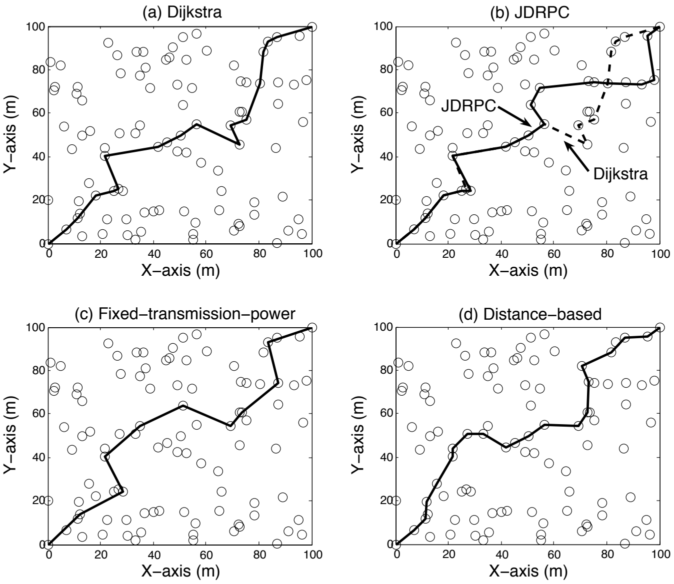

Fig. 4. Typical paths for four routing algorithms

channel conditions. The average power for Distance-based routing is not meaningful because the proportion of successful transmissions is too low (See Table II (c)). In general, when P_{elec} is low, JDRPC can provide up to six times of reduction in power usage, compared to Fixed-transmission-power and Distance-based routing.

Second, we observe that in both Dijkstra and JDRPC, the average hop count for end-to-end transmissions between the same source-sink pair decreases as P_{elec} increases. This matches the intuition in Equation (21) that as P_{elec} increases, a transmitter will try to send packets across a longer distance to reduce the required number of transmissions. Fixed-transmission-power routing is unable to adjust its transmission range, causing average hop counts for different P_{elec} settings to be roughly the same. Distance-based routing favors shorter hops because it only takes distance information into consideration when making routing decisions and adjusting transmission power. Thus it has the largest average hop count among the four schemes.

Third, Table II (c) shows that Dijkstra and JDRPC algorithm have 100% successful end-to-end transmissions for all P_{elec} settings. It is because they always try to transmit packets over wireless links with better link conditions, and adjust transmission power to achieve the optimal *prr*. Contrarily, Fixed-transmission-power routing delivers less than 33% of packets for all P_{elec} settings because it is likely to choose a next hop with very poor link condition. We also observe that Distance-based routing performs very poorly in packet success rate because it makes routing decisions only by distance information, ending up taking more hops with short distances. Traversing across more hops with i.i.d. channels makes it more likely pick poor links along the way, resulting in severe packet losses. This indicates if the power-aware routing is only based on distance information but not realistic channel conditions, it may lead to disastrous network performance. Note that although both Fixed-transmission-power and Distance-based routing are oblivious of channel conditions, the former outperforms the latter. It is because Fixed-transmission-power routing uses larger hop distance R. If we chose a small R, Fixed-transmission-power routing would perform as badly as the Distance-based routing.

As a closer observation, we show typical paths taken by the four routing strategies across the 2-D network in Figure 4. P_{elec} is set to 10^{-3} Watt. In Figure 4(a), Dijkstra algorithm is based on global knowledge of the network, making it able to choose *any* path that leads to minimum expected end-to-end power usage. JDRPC tends to choose its next hop toward the sink, but its ability of making routing decisions and adjusting transmission power to meet the optimal power allocation criteria makes it perform closely to Dijkstra (Figure 4(b)). Contrarily, although Fixed-transmission-power routing does its best by picking a farthest node near its power-optimized transmission boundary, the scheme is unable to adjust transmission power and make routing decisions according to channel states. Figure 4(c) shows that Fixed-transmission-power routing results in hop distances all close to the designated radius R. Distance-based routing chooses short hops and ignores channel conditions, as shown in Figure 4(d). The latter two routing strategies perform poorly.

2) Restricted Adjustment for Transmission Power: Due to the physical limits of power amplifying circuitry and the antenna, transmission power cannot be adjusted arbitrarily. Therefore any given node cannot always obey the fixed-SNR policy for optimal power control. We apply this constraint to nodes in the simulation and observe its impact on end-to-end power cost.

This constraint can be modeled by changing the feasible upper and lower boundaries of the parameter A (refer to (11)). Instead of searching through the whole space from infinitely large transmission power ($SNR \to \infty$, $A = 0$) to infinitely small one ($SNR \to 0$, $A = 1$), we are restricted by choosing A only within the range which physical device limits allow. In the simulation we assume the tunable range of transmission power of each node is between $-15dB$ to $-50dB$. P_{elec} is set to 10^{-3} Watt. Other parameters are the same as those in the previous section. Intuitively, since transmission power cannot be arbitrarily adjusted, a transmitter is not always able to transmit packets efficiently either to a node far away or in the presence of poor channel conditions. In the former case, node density will play an important role because low node density forces a transmitter more likely to transmit packets with poor power efficiency to a long-distant node, resulting in an increase of average power consumption. We simulate Dijkstra, JDRPC, and Fixed-transmission-power algorithm in randomized networks with various number of nodes deployed. Figure 5 and 6 show the trend of average end-to-end power cost and the number of successful end-to-end transmissions for the three routing strategies, respectively. All results are obtained from 10000 random-generated topologies.

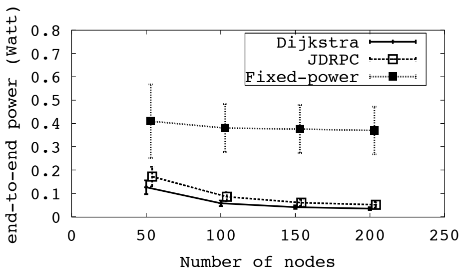

Fig. 5. Average end-to-end power v.s. Node density

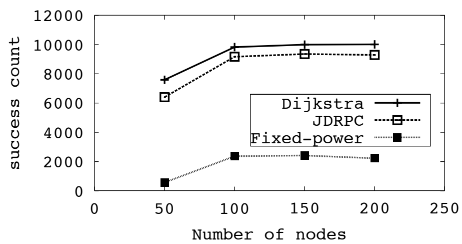

Fig. 6. Successful packet count v.s. Node density

Figure 5 shows that for all three routing schemes, the average power consumption increases as the node density decreases. The reason is for each routing scheme, a transmitter either has fewer neighbors as next-hop candidates, or suffers from being unlikely to locate a neighbor with good channel condition. An inspiring observation of Figure 5 is that for various node densities, JDRPC algorithm performs close to Dijkstra algorithm under the transmission power constraint, and has a huge improvement compared to Fixed-transmission-power routing. It suggests that JDRPC may perform very well compared to the best routing possible practically.

Figure 6 shows that Dijkstra and JDRPC mechanism fail to deliver packets for some end-to-end transmissions, especially when node density is low. The count for successful end-to-end transmissions decreases as the node density decreases. In addition, the difference made by adding extra nodes is significant at low node density. But after some node density level is reached, the marginal performance improvement by adding nodes drops. Under high node density, every node is likely to find a neighbor such that fixed-SNR policy for optimal power control can be achieved even subject to transmission power constraint, which may not be true under low node density.

VII. Conclusion

In this paper, we have proposed a local metric and the corresponding joint power control and routing mechanism in wireless networks. We have first shown that given the electronic power setting and channel conditions, the optimal power allocation over a given link needs to meet a special SNR constant, which can be easily computed by an elegant characteristic equation. Typically, the special SNR constant leads to an optimal per-hop packet reception rate which is high but not close to one. This suggests that the optimal operating point for reliable packet delivery should lie in the transitional region, which is rarely considered in previous research literature. Based on the per-link optimal power control, we have proposed the JDRPC algorithm that utilizes a simple local power-efficiency metric to choose the next hop. Through simulations in linear and 2-D networks, it is shown that JDRPC algorithm can achieve very low average power consumption in different node density settings, compared with the best global strategy possible. Furthermore, JDRPC can provide a great reduction in power usage compared to channel-unaware routing algorithms. We have also shown that JDRPC algorithm also adapts to transmission power limitation of wireless devices.

There are several future research directions to build on this work. First, in this paper we only focus on relatively stable networks. It would be interesting to consider networks with dynamically changing channel conditions and mobility events. Second, MAC schemes play an more important role under high-traffic scenarios. It would be necessary to explicitly design an efficient MAC scheme and incorporate it into the algorithm design. Meanwhile, since the proposed scheme only considers energy efficiency as the major performance metric, it would be interesting to further consider throughput improvement without the loss of energy efficiency.

References

[1] D. Kotz, C. Newport and C. Elliott. The mistaken axioms of wireless-network research. Technical Report TR2003-467, Dept. of Computer Science, Dartmouth College, July 2003.

[2] Karim Seada, Marco Zuniga, Ahmed Helmy, Bhaskar Krishnamachari, "Energy Efficient Forwarding Strategies for Geographic Routing in Wireless Sensor Networks," ACM Sensys, 2004.

[3] D. Ganesan, B. Krishnamachari, A. Woo, D. Culler, D. Estrin and S. Wicker. "Complex Behavior at Scale: An Experimental Study of Low-Power Wireless Sensor Networks". UCLA CS Technical Report UCLA/CSD-TR 02-0013, 2002.

[4] J. Zhao and R. Govindan. "Understanding Packet Delivery Performance in Dense Wireless Sensor Networks". ACM Sensys, November 2003.

[5] A. Woo, T. Tong, and D. Culler. "Taming the Underlying Issues for Reliable Multhop Routing in Sensor Networks". ACM SenSys, November 2003.

[6] D. S. J. De Couto, D. Aguayo, J. Bicket, and R. Morris. "A High-Throughput Path Metric for Multi-Hop Wireless Routing". ACM MobiCom, September 2003.

[7] M. Zuniga and B. Krishnamachari, "Analyzing the Transitional Region in Low Power Wireless Links", IEEE SECON, 2004.

[8] Karp, B. and Kung, H.T., "Greedy Perimeter Stateless Routing for Wireless Networks", ACM MobiCom, August, 2000

[9] M. Mauve, J. Widmer, and H. Hartenstein, "A survey on position-based routing in mobile ad hoc networks," *IEEE Network Magazine*, Vol. 15, No. 6, pp. 30–39, November 2001.

[10] V. Rodoplu and T.H. Meng, "Minimum energy mobile wireless networks," Selected Areas in Communications, IEEE Journal on, vol. 17, Issue 8, August 1999.

[11] R. Wattenhofer, L. Li, P. Bahl, and Y.M. Wang, "Distributed topology control for power efficient operation in multihop wireless ad hoc networks," INFOCOM, April 2001.

[12] S. Narayanaswamy, V. Kawadia, R.S. Sreenivas, and P.R. Kumar, "Power control in ad hoc networks: theory, architecture, algorithm and implementation of the COMPOW protocol," in European Wireless Conference, 2002.

[13] V. Kawadia and P.R. Kumar, "Power control and clustering in ad hoc networks," in *IEEE INFOCOM* 2003.

[14] D. Son, B. Krishnamachari, J. Heidemann, "Experimental study of the effects of Transmission Power Control and Blacklisting in Wireless Sensor Networks," IEEE SECON, 2004.

[15] S. Singh, M. Woo and C. Raghavendra, “Power-Aware Routing in Mobile Ad Hoc Networks,” ACM MobiCom, October 1998.
[16] J.-H. Chang, L. Tassiulas, “Energy Conserving Routing in Wireless Ad-hoc Networks,” IEEE INFOCOM, March 2000.
[17] D. Aguayo, J. Bicket, S. Biswas, G. Judd, and R. Morris, “Link-level measurements from an 802.11b Mesh Network,” SIGCOMM 2004, August 2004.
[18] Theodore S. Rappapport, *Wireless Communications: Principles and Practice*, Prentice Hall.
[19] John G. Proakis, *Ditigal Communications*, McGRAW-HILL.
[20] Kleinrock, L. and J. Silvester, “Optimum Transmission Radii for Packet Radio Networks or why Six is a Magic Number,” Conference Record, National Telecommunications Conference, Birmingham, Alabama, pp. 4.3.2-4.3.5, December 1978.
[21] H. Takagi and L. Kleinrock, “Optimal transmission ranges for randomly distributed packet radio terminals,” IEEE Trans. Commun., vol. COM- 32, Mar. 1984.
[22] T. Hou and V.O. Li, “Transmission range control in multihop packet radio networks,” IEEE Trans. Commun., vol. COM-34, pp. 38-44, Jan. 1986.
[23] R. Ramanathan, R. Rosales-Hain, “Topology Control of Multihop Wireless Networks using Transmit Power Adjustment,” IEEE INFOCOM, March 2000.
[24] W. Ye, J. Heidemann, and D. Estrin, An energy-efficient MAC protocol for wireless sensor networks, IEEE INFOCOM, June 2002.