Distributed Spectrum-Efficient Routing Algorithms in Wireless Networks

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***Abstract*— This paper applies spectral efficiency as a performance measure for routing schemes and considers how to obtain a good route in a wireless network as the network signal-to-noise ratio (SNR) varies. The motivation for this study is to combine different wireless routing perspectives from networking and information theory.**

The problem of finding the optimum route with the maximum spectral efficiency is difficult to solve in a distributed fashion. Motivated by an information-theoretical analysis, this paper proposes two suboptimal alternatives, namely, the approximately ideal path routing (AIPR) scheme and the distributed spectrum-efficient routing (DSER) scheme. AIPR finds a path to approximate an optimum regular path that might not exist in the network and requires location information. DSER is more amenable to distributed implementations based on Bellman-Ford or Dijkstra's algorithms. The spectral efficiency of AIPR and DSER for random networks approaches that of nearest-neighbor routing in the low SNR regime and that of direct communication in the high SNR regime. Around the regime of 0 dB SNR, the spectral efficiency of DSER is up to twice that of nearest-neighbor routing or direct communication.

I. Background and Motivation

As wireless communications are extended beyond the last hop of networks, new paradigms for wireless relaying (including routing as a special case), are needed to address unique demands, *e.g.*, spectral efficiency, of multi-hop wireless networks. Research from different perspectives, namely, networking and information theory, often results in different, sometimes even conflicting, routing paradigms for wireless networks [1]–[7]. The goal of this paper is to study the wireless routing problem combining networking and information-theoretic perspectives.

The study of wireless networks using information theory [1]–[4] has led to many relaying protocols that are asymptotically order-optimal as the number of nodes goes to infinity. However, all practical networks have a finite number of terminals. Furthermore, relaying protocols from information theory can involve complicated multiuser coding techniques, such as block-Markov coding and successive interference cancellation, which are often not allowed in practical systems. The gap between information theoretical analyses and practical implementations has inspired us to study networks with a finite number of nodes with an emphasis on the distributed implementation aspects of our routing schemes.

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On the other hand, most previous work on routing from the network community, *e.g.*, [6], [7] mainly studies how to design new routing metrics to improve the throughput, and how to modify existing routing protocols to incorporate new metrics. Their models are often built on link-level abstractions of the network without fully considering the impact of the physical layer. There is little if any discussion about the fundamental performance limits, namely (Shannon) capacity or spectral efficiency. In contrast to these works, this paper studies the influences of different routing schemes on spectral efficiencies and designs distributed routing schemes based on insights from an information-theoretical analysis.

The work in [8]–[10] provides important guidelines for designing spectrum-efficient networks. Assuming a one-dimensional linear network, [8]–[10] show that there is an optimum number of hops in terms of maximizing end-to-end spectral efficiency. The results challenge the traditional wireless routing paradigm of "the more hops the better". However, [8]–[10] assume the number of relay stations and their locations are design parameters. In practice, the network geometry changes as the network operates and grows; thus, neither the number of available relay nodes nor their location between a source and destination are design parameters. Therefore, this paper considers choosing the optimum route in a network comprised of an arbitrary number of randomly located nodes.

The remainder of the paper is organized as follows. Section II describes the system model and assumptions. Section III formulates the problems of finding a route with the maximum spectral efficiency assuming the optimal bandwidth allocation and equal bandwidth sharing, respectively. Since bandwidth allocation requires exchange of global information, the rest of the paper focuses on providing solutions for the case of equal bandwidth sharing. Section IV proposes the AIPR scheme, which requires location information. Section V proposes the DSER scheme as another suboptimal solution to the problem in Section III. The spectral efficiency of DSER closely follows the optimal spectral efficiency as the network SNR changes. More importantly, relative to AIPR, DSER can be implemented with standard distributed algorithms that are guaranteed to converge and generate loop-free paths. Section VI presents simulation results and Section VII concludes the paper.

II. System Models

A. Network model

We represent the nodes in a network and the possible transmissions between nodes by a directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where $\mathcal{V}$ represents the set of nodes in the network and $\mathcal{E}$ represents the set of directed edges (links). For each link $e \in \mathcal{E}$, we use $t(e)$ to represent the transmit end of the link and $r(e)$ to be the receive end. A path L from node s to node d, $s \neq d$, consists of an ordered sequence of unique links $l_1, l_2, l_3, ..., l_n \in \mathcal{E}$ that satisfies the following: for each $1 \leq k \leq n-1$, $r(l_k) = t(l_{k+1})$; $t(l_1) = s$; and $r(l_n) = d$. We also denote the source and destination of a given path L as $t(L) = t(l_1)$ and $r(L) = r(l_n)$, respectively. The length of the path $|L|$ is the number of links in the path. One typical assumption in networks is that there is no link between two terminals if the signal quality is below certain thresholds [1], [6], [7]. However, from an information theoretical perspective, two terminals can always communicate with a sufficiently low rate. Therefore, in this paper we assume any two terminals in the network can directly communicate.

B. Channel Model

The wireless signal is attenuated with a power decay law that is inversely proportional to the α-th power of the distance between the transmitter and the receiver. Thus, the path-loss factor from node i to node j is given by

$$G_{i,j} = cD_{i,j}^{-\alpha}, \tag{1}$$

where $D_{i,j}$ is the Euclidean distance between node i and j, α is the path loss exponent (typically taking values between 2 and 4), and c is a constant. We can also express $G_{i,j}$ as G_l where $l \in \mathcal{E}$, $t(l) = i$, $r(l) = j$. This model holds only when $cD_{i,j}^{-\alpha} \ll 1$. In this paper, after appropriately normalizing the transmission power, we will assume that $c = 1$. The received signal is also corrupted with additive white Gaussian noise (AWGN) with a normalized one-sided power spectral density N_0, which is assumed to be the same for all receivers.

We consider the setting in which all transmit devices are constrained by the same symbol-wise average transmit power P and assume all devices transmit with the maximum available power P. This assumption is justified by the fact that for the low-power transceivers, the local oscillators and bias circuitry dominate the energy consumption [11]. Another observation in support of this assumption is that terminals in wireless mesh networks are mostly immobile and connected with abundant power supplies. We further assume that the network is supplied with a finite bandwidth B (Hz) and define the normalized network SNR as

$$\rho = \frac{P}{N_0 B}, \tag{2}$$

For any link $l \in \mathcal{E}$ that connects node i and j, we define the link SNR on link l as

$$\rho_l = \rho G_l, \tag{3}$$

where G_l is the path-loss factor along the link. We define the spectral efficiency R_L for a path L as the bandwidth-normalized end-to-end rate, *i.e.*, $R_L = C_L/B$ bits per channel use, where C_L is the end-to-end achievable rate in bits per second given a bandwidth constraint B along the path L. The average spectral efficiency of a routing scheme is the spectral efficiency of its selected routing path averaged over random networks.

C. Scheduling

Because wireless devices generally cannot transmit and receive at the same time on the same frequency, it is important to schedule the transmission of terminals to avoid such conflicts. In general, scheduling transmission in networks is NP-hard [12]. To avoid the difficulty of jointly optimizing routing and scheduling, we assume the network operates with time division multiple access (TDMA) without spatial reuse, *i.e.*, each node transmits in its own unique time slot. Thus, there is no interference at any receiver.

For simplicity, we only consider routing for one source-destination pair and limit our study to single-path routing as most existing routing protocols do not exploit multi-path routing. Also we do not allow the links to exploit cooperative diversity, *e.g.*, [13], [14].

III. Problem Formulations

This section discusses how to select routing paths that maximize the spectral efficiency. If bandwidth optimization is allowed, Section III-A provides the optimal routing scheme. For the case of equal bandwidth sharing, Section IV shows that the optimal routing path is difficult to find and inspires Section IV and Section V for suboptimal solutions.

A. Bandwidth Optimization

Along a path L, we denote the fraction of channel uses allocated to each link l as λ_l. Due to the global constraint on bandwidth, we have

$$\sum_{l \in L} \lambda_l = 1.$$

If the network permits bandwidth optimization over λ_l, [9] shows the max-min spectral efficiency along a route L is

$$\frac{1}{\sum_{l \in L} \frac{1}{\log(1+\rho_l)}},$$

for

$$\lambda_l = \frac{1}{\log(1+\rho_l) \sum_{i \in L} \frac{1}{\log(1+\rho_i)}}. \tag{4}$$

Therefore, we can use Bellman-Ford or Dijkstra's algorithms with a link metric of $1/\log(1+\rho_l)$ to find the route that maximizes the spectral efficiency by minimizing $\sum_l (1/\log(1+\rho_l))$. We refer to such a routing scheme as optimal routing with bandwidth optimization (ORBO). Although the ORBO path can be computed in a distributed way, the optimal bandwidth share of link l requires each node to know the link SNRs of the whole route to compute. As we will see, ORBO is most beneficial in the low SNR regime, where the power spent in distributing global knowledge of routes may not be neglected. Another concern about bandwidth optimization is the issue of fairness, as one node with a larger share of the bandwidth might spend more energy than other nodes with a smaller share of the bandwidth. Therefore, the rest of the paper focuses on the case of equal bandwidth sharing.

B. Equal Bandwidth Sharing

Under the constraint of equal bandwidth sharing, the end-to-end spectral efficiency of a given path L is

$$R_L = \min_{l \in L} \frac{1}{|L|} \log(1 + \rho_l), \tag{5}$$

where the factor $1/|L|$ comes from the sharing of bandwidth among relay links. For a path L, the signal quality is reflected by the worst link signal SNR $\rho_L^* = \min_{l \in L} \rho_l$, and the efficiency of bandwidth use is characterized by $|L|$. The spectral efficiency (5) increases as ρ_L^* increases or $|L|$ decreases. However, for routes connecting a given source and destination, if the number of links $|L|$ increases (or decreases), there are more (or less) relay nodes and ρ_L^* is more likely to increase (or decrease) due to shorter (longer) inter-relay distances. This can be seen by comparing the nearest-neighbor route and the direct communication (the source directly transmits to the destination) in a linear network. For all routes connecting a given source and destination, the nearest-neighbor route has the maximal ρ_L^* but also the largest $|L|$. On the other hand, direct communication has the minimal ρ_L^*, but also has the smallest $|L|$. Therefore, there is a trade-off between physical layer parameters, *i.e.*, signal quality and the efficiency of bandwidth use, in selection of routes. The optimal routing scheme takes this trade-off into account by providing a solution to the following optimization problem:

$$\max_{L: r(L)=s, t(L)=d} \; \min_{l \in L} \frac{1}{|L|} \log(1 + \rho_l), \tag{6}$$

where nodes s and d form the desired source-destination pair.

Unfortunately, the routing metric given in (5) is neither isotonic nor monotone [15], [16]. Therefore, generalized Bellman-Ford and Dijkstra's algorithms cannot be used to solve (6). In general, the computation of the spectral efficiency by (5) requires global information about a path. Therefore, the problem (6) does not exhibit the optimal substructure that is necessary for the use of dynamic programming methods [17]. The solution to (6) can in principle be obtained by an exhaustive search method. However, for a network with n relays, there are 2^n different possible paths connecting the source and destination. This exponential growth makes the exhaustive search method unrealistic in practice if the network has a moderate to large number of relay nodes. More importantly, an exhaustive search method is not amenable to distributed implementation. Therefore, in the following, Section IV and Section V provides two alternative suboptimal solutions to (6).

IV. Approximately Ideal Path Routing (AIPR)

The idea of AIPR is to find a route that approximates the optimal regular linear path. For a regular linear path, [8] suggests that there is an optimum number of hops n_{opt}. More specifically, in [8], it is shown that the number of links along an optimal path satisfies

$$n_{opt} R \approx \frac{\alpha + \mathcal{W}(-\alpha e^{-\alpha})}{\ln 2}, \tag{7}$$

where R is the path spectral efficiency, and $\mathcal{W}(\cdot)$ is the principal branch of the Lambert *W* function [18]. Furthermore, from (1) and (5), we have the following condition for an optimal regular linear path given the network SNR ρ,

$$n_{opt} \approx \left(\frac{2^{n_{opt} R} - 1}{\rho} \right)^{1/\alpha}. \tag{8}$$

Plugging (7) into (8), we obtain the number of hops in an optimal regular linear path.

Thus, given the network SNR ρ, we can compute the optimum inter-relay distance D_{hop}, which is equal to the total source-destination distance divided by n_{hop}. However, such a regular linear path with an optimum inter-relay distance might not exist in the network. A suboptimal solution to (6) can be obtained by finding a path approximating this ideal path. We propose the following procedure to obtain an approximately ideal path:

1) Calculate the optimum inter-relay distance D_{hop};
2) Find the next-hop node which is at most D_{hop} away from the source and lies within the angle $\phi/2, 0 \le \phi \le \pi$ of the axis from the source to the destination;
   a) If there is no such node, increase D_{hop} until there is a such node;
   b) If there is more than one such node, choose one with the maximum distance from the source;
3) Continue 2) using the chosen relay as the new source and the possibly new D_{hop} until the destination is reached.

Note that the parameter $\phi/2$ is chosen to prevent the path from going in the wrong direction in the two-dimensional plane. Since the motivation for this scheme is to approximate the ideal path, we refer to this routing scheme as the approximately ideal path routing (AIPR). The implementation of AIPR requires location information. Therefore, this approach is not easy to integrate into existing network routing protocols based on Bellman-Ford or Dijkstra's algorithms. In the following, we will propose another suboptimal solution to (6) that is more amenable to distributed implementation.

V. Distributed Spectrum-Efficient Routing (DSER)

The discussion in Section III suggests that there is both a penalty and a reward, in terms of spectral efficiency, with addition of intermediate relay links. This motivates us to solve the following problem for a spectrum-efficient route:

$$\min_{L: r(L)=s, t(L)=d} \; \sum_{l \in L} 1 + \frac{\beta}{\rho_l}, \tag{9}$$

where, as before, nodes s and d form the desired source-destination pair, and $\beta \ge 0$, referred to as the *routing coefficient*, is a parameter that can be designed. Intuitively, the additive constant 1 represents the penalty for additional hops on corresponding efficiency of bandwidth use; the factor $1/\rho_l$ characterizes SNR gains by using links with short distances;

and the parameter β weights the impact of power and bandwidth. A routing scheme can use $1 + \beta/\rho_l$ as the link metric and use distributed Bellman-Ford or Dijkstra's algorithms to solve (9). As we will see, this routing scheme can offer significant gains in spectral efficiency compared to nearest-neighbor routing or direct communication. For this reason, we refer to this routing scheme as the *distributed spectrum-efficient routing* (DSER) scheme. The DSER scheme does not depend on the particular path-loss model in (1). In practice, the link SNR can be directly measured by received signal strength indicators (RSSI) available on most devices and fed back to the transmitters. As a last remark, DSER is backward compatible, *i.e.*, by choosing $\beta = 0$, DSER degrades to the traditional routing scheme using the additive hop count metric.

A. Values of the Routing Coefficient

To determine the routing coefficient β, we note that (8) provides the optimum number of hops n_{opt} for the design of a regular linear network. Now, if we assume that DSER is used to design a regular linear network connecting a particular source-destination pair with SNR ρ, the minimization objective function becomes

$$f(|L|) = |L| \left[1 + \frac{\beta |L|^{-\alpha}}{\rho}\right]. \tag{10}$$

We temporarily treat $|L|$ as a real number, differentiate (10) with respect to $|L|$ and set $df(|L|)/d|L| = 0$ to obtain an expression for the optimum number of links $|L|_{opt}$. By letting $|L|_{opt} = n_{opt}$, we have

$$\beta = \frac{e^{\alpha + \mathcal{W}(-\alpha e^{-\alpha})} - 1}{\alpha - 1}. \tag{11}$$

The routing coefficient determined by (11) is independent of the network SNR and can be determined by the channel model. Furthermore, in the range $1 \leq \alpha \leq 5$, (11) can be very accurately approximated as $\beta \approx 2^\alpha$. In Section VI we present simulation results to show that DSER performs quite well using this approximation.

We note that (11) is developed assuming there are an infinite number of nodes and locations from which to choose. Therefore, for an arbitrary network with a finite number of nodes, the value of β can be further tuned, *e.g.*, for a specific route geometry and network SNR, to improve the spectral efficiency of the DSER scheme.

B. Properties

From (9), it is straightforward to see that for a given network, the route generated by DSER depends on the link SNRs. In the high SNR regime, the term β/ρ_l in (9) can be much smaller than the penalty term 1, *i.e.*, the cost of sharing bandwidth among many links outweighs the SNR gains of shorter inter-relay distances. Thus, the DSER route will approach direct communication between the source and destination in this regime. In the low SNR regime, the term β/ρ_l becomes the dominant term in the link metric, *i.e.*, the SNR gains of shorter links outweigh the cost of sharing bandwidth. In such scenarios, the performance of DSER will approach that of nearest-neighbor routing. The discussion here agrees with simulation results we will present in Section VI.

For the DSER scheme, the weight of a path L is $W(L) = \sum_{l \in L} 1 + \beta/\rho_l$. For any paths L_1, L_2, L_3, if $W(L_1) < W(L_2)$, we have both $W(L_1 \oplus L_3) < W(L_2 \oplus L_3)$ and $W(L_3 \oplus L_1) < W(L_3 \oplus L_2)$, where $L_1 \oplus L_2$ denotes the concatenation of two paths L_1 and L_2. Thus, the DSER metric is strictly isotonic [15]. Moreover, for any paths L_1, L_2, we have $W(L_1) \leq W(L_1 \oplus L_2)$, *i.e.*, the DSER metric is monotone [16]. It has been shown [15] that for link-state routing protocols, isotonicity of the path weight function is a necessary and sufficient condition for a generalized Dijkstra's algorithm to yield optimal paths. If the path weight function satisfies strict isotonicity, forwarding decisions can be based only on independent local computation, and the resulting path is loop free. For path vector routing protocols, monotonicity of the path weight function implies protocol convergence in every network, and isotonicity assures convergence of algorithms into optimal paths [16]. Therefore, the DSER scheme can be implemented in existing networks with link-state or path vector routing protocols. Also, the path metric of the DSER scheme is additive, meeting a standard assumption of most existing implementations of Bellman-Ford or Dijkstra's algorithms [17].

VI. Simulation Results

This section presents simulation results to compare spectral efficiencies of different routing schemes. As spectral efficiencies grow with SNR in general, the absolute difference between the spectral efficiencies of two routing schemes may not reflect their relative performance difference. Therefore, we compare different routing schemes using direct communication as the reference. More specifically, we define the normalized spectral efficiency ratio γ of a routing scheme as the ratio of its average spectral efficiency R to the average spectral efficiency of direct communication, *i.e.*, $\gamma = R/\log(1 + \rho)$. For two routing schemes A and B with ratios γ_A, γ_B, respectively, the difference between two ratios, *i.e.*, $\gamma_A - \gamma_B$, reflects the ratio of spectral efficiency difference of two routing schemes to the spectral efficiency of direct communication.

Our simulations focus on uniformly random linear networks. We assume the source and destination are located at coordinates $(0, 0)$ and $(1, 0)$, respectively, and the horizontal coordinates of intermediate relay nodes are independent random variables uniformly distributed between 0 and 1. We assume a path-loss model described in Section II-B, taking the path loss exponent α as 4. According to the approximation $\beta \approx 2^\alpha$ in Section V, the routing coefficient is taken to be 16. We average over 10^5 network realizations. In our simulations, the boundaries of the 90% confidence interval are within $\pm 1\%$ of the average value assuming the spectral efficiency of a routing scheme is Gaussian distributed. Thus, the confidence interval is sufficiently-small, allowing us to compare routing schemes using the average spectral efficiency, or equivalently, the normalized spectral efficiency ratio.

As two examples, Fig. 1 and Fig. 2 show the average normalized spectral efficiency ratios of different routing schemes including nearest-neighbor routing, direct communication, AIPR, and DSER for uniformly random linear networks with 5 and 10 nodes, respectively. In Fig. 1 and Fig. 2, the optimal spectral efficiency is obtained by an exhaustive search method and is provided as a reference. It is clear that the performance of direct communication only approaches the optimum performance in the high SNR regime and suffers from a significant loss in spectral efficiency at low SNR. The performance of nearest-neighbor routing approaches the optimal performance in the low SNR regime, but degrades in the high SNR regime due to its inefficient use of bandwidth. In contrast, one can observe that the curves of the DSER scheme track the optimal curves throughout the whole SNR regime. One can also note that the AIPR scheme is also capable of adapting to the change of network SNRs. In the low SNR regime, AIPR might outperform nearest-neighbor routing and DSER. However, in the moderate SNR regime, DSER offers significant gains in spectral efficiency relative to AIPR, nearest-neighbor routing, and direct communication. In particular, when the network SNR is around 0 dB, the spectral efficiency of the DSER scheme is twice as large as those of nearest-neighbor routing and direct communication. Therefore, networks can benefit significantly in spectral efficiency from the use of DSER. Also, comparing Fig. 1 to Fig. 2, it is observed that, as the number of nodes increases, the performance of DSER and AIPR generally improves regardless of SNR regimes. However, as the number of users grows, the performance of nearest-neighbor routing improves in the low SNR regime and degrades in the high SNR regimes.

Another important observation for Fig. 1 and Fig. 2 is that the normalized ratio of each routing scheme approaches two different constants at low and high SNRs. This observation suggests different scaling behavior at different SNR regimes. Recall that at low SNR, the spectral efficiency of direct communication is approximated by ρ. Thus, the observation that the normalized ratio of a routing scheme approaches a constant at low SNR suggests the average spectral efficiency of this routing scheme scales linearly with SNR at low SNR. We characterize this scaling behavior by the coding gain, defined as $\tau := \lim_{\rho\to 0}\gamma$. The coding gain τ is the slope of the curve of the spectral efficiency as a function of SNR at low SNR. From Fig. 1 and Fig. 2, the coding gain of DSER is close to that of nearest-neighbor routing and inferior to AIPR and optimal routing, indicating AIPR is better than DSER at low SNR. At high SNR, the spectral efficiency of direct communication is approximated by $\log\rho$. Thus, the observation that the normalized ratio of a routing scheme approaches a constant at high SNR suggests the average spectral efficiency of this routing scheme scales linearly with the logarithm of SNR at high SNR. Following [19], we can define the network multiplexing gain as $\eta := \lim_{\rho\to\infty}\gamma$. The multiplexing gain η reflects the degrees of freedom that are utilized by a routing scheme, and is the slope of the curve of the spectral efficiency as a function of the logarithm of SNR at high SNR. Fig. 1 and Fig. 2 show that direct communication, DSER, AIPR and optimal routing all approach the multiplexing gain 1. In contrast, nearest-neighbor routing suffers from a significant loss in channel degrees of freedom due to a small multiplexing gain.

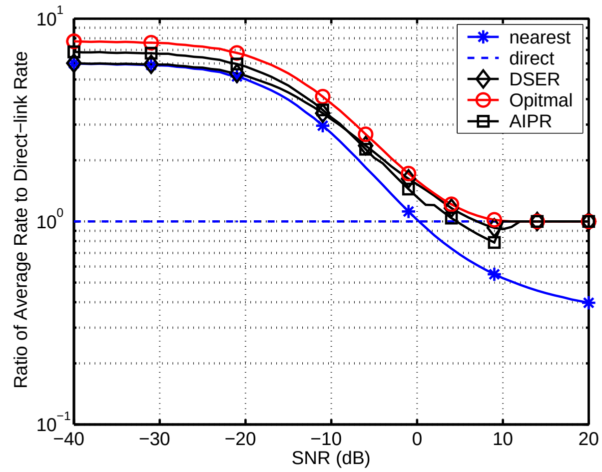

Fig. 1. Normalized spectral efficiency ratio of different routing schemes for uniformly random linear networks with 5 nodes.

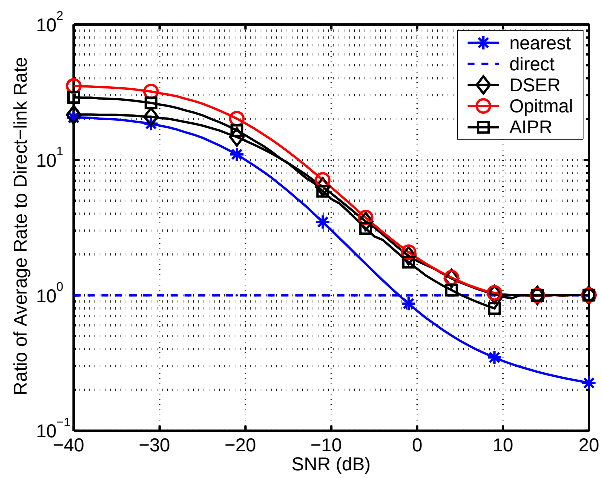

Fig. 2. Normalized spectral efficiency ratio of different routing schemes for uniformly random linear networks with 10 nodes.

Fig. 3 compares the performance of DSER with that of optimal routing with bandwidth optimization (ORBO). The spectral efficiency improves for ORBO mainly in the low SNR regime. However, as the network SNR increases, the benefit of bandwidth optimization decreases and eventually vanishes. This is because at high SNR, the ORBO route is direct communication, which is also the case for the DSER path.

VII. Conclusion

This paper studies end-to-end spectral efficiencies of different wireless routing schemes. This paper's main contribution is to introduce two suboptimal solutions, namely, approximately ideal path routing (AIPR) and distributed spectrum-efficient routing (DSER), to the problem of finding routes with high spectral efficiency. AIPR is a location-assisted routing scheme. DSER can be based upon local link quality estimates, can

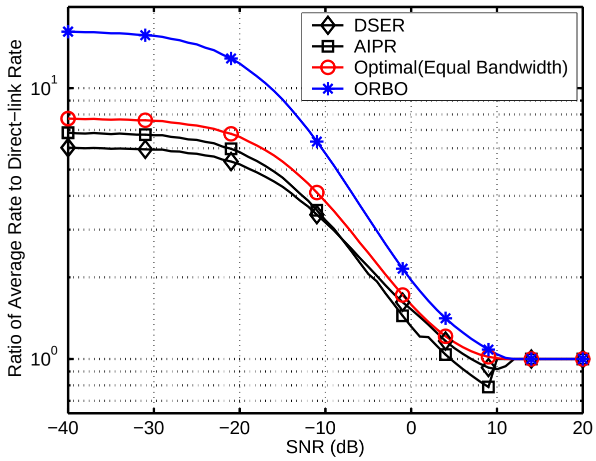

Fig. 3. Normalized spectral efficiency ratio of the optimal routing with bandwidth optimization (ORBO) and DSER for uniformly random linear networks with 5 nodes.

be implemented using standard Bellman-Ford or Dijkstra's algorithms, and can be integrated into existing network protocols. Our results indicate that the spectral efficiency of DSER scales linearly with SNR at low SNR and scales linearly with the logarithm of SNR at high SNR. Furthermore, the performance of DSER is close to that of popular nearest-neighbor routing and that of minimum hop-count routing in the low and high SNR regimes, respectively. In the moderate SNR regime, DSER provides significant gains in spectral efficiency compared with both nearest-neighbor routing and minimum hop-count routing. Therefore, wireless mesh networks and wireless sensor networks can benefit significantly from using DSER.

References

[1] P. Gupta and P. Kumar, "The capacity of wireless networks," *IEEE Trans. Inform. Theory*, vol. 46, no. 2, pp. 388–404, 2000.

[2] M. Gastpar and M. Vetterli, "On the Capacity of Large Gaussian Relay Networks," *IEEE Trans. Inform. Theory*, vol. 51, no. 3, pp. 765–779, Mar. 2005.

[3] G. Kramer, M. Gastpar, and P. Gupta, "Cooperative Strategies and Capacity Theorems for Relay Networks," *IEEE Trans. Inform. Theory*, vol. 51, no. 9, pp. 3037–3063, Sept. 2005.

[4] L.-L. Xie and P. Kumar, "A network information theory for wireless communication: Scaling laws and optimal operation," *IEEE Trans. Inform. Theory*, vol. 50, no. 5, pp. 748–767, May 2004.

[5] X. Hong, K. Xu, and M. Gerla, "Scalable routing protocols for mobile ad hoc networks," *IEEE Network Magazine*, pp. 11–21, July/August 2002.

[6] D. S. J. D. Couto, D. Aguayo, J. Bicket, and R. Morris, "A high-throughput path metric for multi-hop wireless routing," in *Proc. ACM MOBICOM*, 2003.

[7] R. Draves, J. Padhye, and B. Zill, "Routing in multi-radio, multi-hop wireless mesh networks," in *Proc. ACM MOBICOM*, 2004.

[8] M. Sikora, J. N. Laneman, M. Haenggi, J. D. J. Costello, and T. E. Fuja, "Bandwidth- and Power-Efficient Routing in Linear Wireless Networks," *Joint Special Issue of IEEE Trans. Inform. Theory and IEEE Trans. Networking* , vol. 52, no. 6, pp. 2624–2633, June 2006.

[9] Ö. Oyman and S. Sandhu, "A Shannon-Theoretic Perspective on Fading Multihop Networks," in *Proc. Conf. Inform. Sci. and Syst. (CISS)*, 2006.

[10] ——, "Non-Ergodic Power-Bandwidth Tradeoff in Linear Multi-hop Networks," in *Proc. IEEE Int. Symp. Information Theory (ISIT)*, 2006.

[11] M. Haenggi and D. Puccinelli, "Routing in ad hoc networks: A case for long hops," *IEEE Communications Magazine*, vol. 43, pp. 93–101, Oct. 2005.

[12] B. Hajek and G. Sasaki, "Link scheduling in polynomial time," *IEEE Trans. Inform. Theory*, vol. 34, no. 5, pp. 910–917, 1988.

[13] A. Sendonaris, E. Erkip, and B. Aazhang, "User Cooperation Diversity, Parts I & II," vol. 15, no. 11, pp. 1927–1948, 2003.

[14] J. N. Laneman, D. N. C. Tse, and G. W. Wornell, " Cooperative Diversity in Wireless Networks: Efficient Protocols and Outage Behavior," *IEEE Trans. Inform. Theory*, vol. 50, no. 12, pp. 3062–3080, December 2004.

[15] J. L. Sobrinho, "Algebra and Algorithms for QoS Path Computation and Hop-by-Hop Routing in the Internet," *IEEE/ACM Trans. Networking*, vol. 10, no. 4, pp. 541–550, 2002.

[16] ——, "An Algebraic Theory of Dynamic Network Routing," *IEEE/ACM Trans. Networking*, vol. 13, no. 5, pp. 1160–1173, 2005.

[17] T. H. Cormen, C. E. Leiserson, R. L. Rivest, C. S. Abramowitz, and I. A. Stegun, *Introduction to Algorithms*. The MIT Press and McGraw-Hill, 2001.

[18] R. M. Corless, G. H. Gonnet, D. E. G. Hare, D. J. Jeffrey, and D. E. Knuth, "On the Lambert W Function," *Adv. Computational Maths*, vol. 5, pp. 329–359, 1996.

[19] L. Zheng and D. N. C. Tse, "Diversity and Multiplexing: A Fundamental Tradeoff in Multiple-Antenna Channels," *IEEE Trans. Inform. Theory*, vol. 49, no. 5, pp. 1073–1096, May 2003.