A Bio-Inspired Transmit Power Control Algorithm for Linear Multi-Hop Wireless Networks

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***Abstract*—Inspired by the flocking behavior, we propose a distributed transmit power control (TPC) algorithm for maximizing the end-to-end rate in a linear multi-hop wireless network. As each bird in flock goes to match its velocity with the average velocity of its neighbors in a distributed manner, each node on the multi-hop path matches its transmission rate with the average transmission rate of its neighbor nodes by controlling its transmit power. We verify that this TPC algorithm performing a local rate-average strategy maximizes the end-to-end rate of the wireless multi-hop link. Simulation results show that as with the flocking algorithm, the proposed TPC algorithm enables all link rates to converge to the same value, and also significantly decreases the power consumption of multi-hop nodes, while maximizing the multi-hop end-to-end rate.**

Keywords-transmit power control; bio-inspired algorithm; flocking algorithm; end-to-end rate maximization; multi-hop network

I. Introduction

In multi-hop networks, an increase in the number of hops improves each link budget, but generates more traffic in the network. This eventually increases the access collision and interference levels and so degrades the multi-hop end-to-end performance [1]. The most effective method for breaking through this trade-off is a transmit power control (TPC) that controls the transmit power of multi-hop nodes in order to mitigate the strong interference while ensuring a reasonable link budget [2].

The typical TPC algorithms in wireless multi-hop networks are mainly based on the condition of individual links [3]-[10]. In [3]-[5], the minimum transmit power level is used to guarantee the signal-to-interference plus noise ratio (SINR) required at the receiving node depending on the quality of service (QoS) of the transmitted packets, aiming at achieving not only interference mitigation but also power saving. In [6] and [7], the transmit power is controlled based on the packet size. The greater is the packet size, the higher is the packet error rate (PER); the transmit power increases with an increase in the packet size. In [8], the transmit power is determined based on the channel state information (CSI) to maintain a constant bit error rate (BER) at the receiver. In [9], the transmit power for control packets increases to prevent interference from hidden nodes in the IEEE 802.11 system. In [10], a common power level is determined from the perspective of the overall network capacity in order to guarantee the rates of bi-directional links.

The objective of typical TPC algorithms in wireless multi-hop networks is mostly to minimize the transmit power consumption while ensuring the given QoS (i.e., SINR or BER) of each individual link on the multi-hop path [2]. Such a power minimization problem subject to the constant SINR requirement can guarantee the required end-to-end rate of a multi-hop link, but cannot maximize it, because the achievable maximum SINR value that maximizes the end-to-end rate of a given multi-hop link is unknown. This achievable maximum SINR value varies depending on the transmit power of each multi-hop node due to the mutual interference among wireless links. Therefore, the transmit powers of all nodes should be considered jointly to maximize the end-to-end rate in a given inter-link interference situation. However, this joint TPC operation requires a complex calculation and causes a significant overhead for sharing information among all nodes to determine the optimal transmission power in each node [1].

To solve such a complex optimization problem, in this paper, we pay attention to a biological system known as the *flocking behavior*, which is exhibited when a group of birds, called a flock, are foraging or in flight. Flocks behave with a very simple rule in complex, unstructured, and dynamically changing environments, but they show a emergent behavior achieving their common goal robustly and efficiently. By understanding the similarities between the flocking behavior and the wireless multi-hop transmission, we adapt the underlying principles of the flocking behavior to the TPC algorithm in wireless multi-hop networks. As the flocking algorithm operates in simple and distributed manners and shows converged phenomena, the proposed bio-inspired TPC (BiTPC) algorithm follows a low-complex operation without a centralized controller and converges to maximize the end-to-end rate in the considered linear multi-hop network.

The rest of this paper is organized as follows. In Section II, we describe the optimization problem for maximizing the end-to-end rate in the linear multi-hop wireless network. In Section III, we introduce the flocking behavior and mention its properties. In Section IV, we explain the proposed BiTPC algorithm in detail. In Section V, we investigate the optimality of the proposed BiTPC algorithm. In Section VI, we discuss

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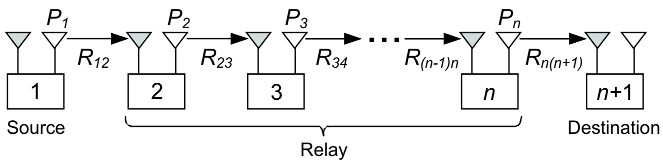

Figure 1. Considered linear multi-hop wireless network.

the simulation results. Finally, we conclude the paper in Section VII.

II. Problem Description

Fig. 1 shows a considered linear multi-hop wireless network consisting of n hops from a source to a destination. Here, we define some notation, as follows:

- P_i: transmit power of node i
- N_i: noise power at node i
- I_i: interference power received at node i
- g_{ij}: channel gain from node i to node j
- SINR_{ij}: SINR from node i to node j
- R_{ij}: link rate from node i to node j

By max-flow min-cut theorem, the end-to-end rate from the source node to the destination node is determined by the smallest value of the link rates in the multi-hop [11]. Therefore, it is defined as

$$R_{e2e} := \min\{R_{12}, R_{23}, \cdots, R_{n(n+1)}\}. \tag{1}$$

Our objective is to obtain the transmit powers of all the transmitting nodes that maximize the end-to-end rate R_{e2e}. This is described as the following optimization problem:

$$\max_{\mathbf{P}} R_{e2e} = \max_{\mathbf{P}} \min\{R_{12}, R_{23}, \cdots, R_{n(n+1)}\} \tag{2}$$

$$\text{s.t.} \quad \mathbf{P} = [P_1 P_2 \cdots P_n] \tag{3}$$

$$\begin{aligned} R_{ij} &\le \log_2(1+\text{SINR}_{ij}) \text{ for } i=1,2,\cdots,n \text{ and } j=i+1 \\ &= \log_2\left(1+\frac{P_i g_{ij}}{I_j+N_j}\right) \\ &= \log_2\left(1+\frac{P_i g_{ij}}{\sum_{\forall k\neq i,j} P_k g_{kj} + N_j}\right) \text{[b/s/Hz]} \end{aligned} \tag{4}$$

$$P_i \le P_{max} \quad \text{for } i=1,2,\cdots,n \tag{5}$$

where $\mathbf{P}$ is the vector of the transmit power of each node, P_{max} is the maximum transmit power constraint, and I_j is given by $\sum_{\forall k\neq i,j} P_k g_{kj}$ as the sum of interferences from other transmitting nodes that use the same radio resource. Here, we assume that all nodes use the same resource without considering a particular scheduling because our main purpose is to show the applicability of the proposed BiTPC algorithm under the inter-link interference condition. In this context, we also assume that the relay node is a full-duplex relay; therefore, it is possible to receive and transmit packets simultaneously without self-interference and processing delay [12]. It should be noted that the considered optimization problem is complicated to solve directly (i.e., it is not convex) because the transmit power of each node affects all link rates.

III. Flocking Behavior

Flocking represents the phenomenon in which self-propelled individuals organize into an ordered motion by using only limited environmental information and simple rules. For example, a flock of birds whose members are moving in $\mathbb{R}^3$ shows that the state of the flock converges to one in which all birds fly with the same velocity. The simple rule of this flocking behavior is known that each bird autonomously adjusts its velocity according to the velocities of its neighbors. The recent representative Cucker-Smale flocking model [13] explains the flocking behavior, that is, at time t and for bird i, every bird adjusts its velocity v_i as follows:

$$v_i(t+1) - v_i(t) = \frac{\lambda}{N}\sum_{j=1}^{N}\psi(|x_j - x_i|)(v_j - v_i) \tag{6}$$

where N is the number of birds, λ is a coupling strength as a learning parameter, and x_i is the position of bird i. ψ means a communication range function which can be set to $\psi(|x_j - x_i|) = 1$ only in case of $|x_j - x_i| \le r$. So, this flocking rule can be interpreted as a local averaging algorithm for bird velocity. In addition, Cucker-Smale flocking model ensures that an interacting N-particle system $\{(x_i(t), v_i(t))\}_{i=1}^{N}$ has time-asymptotic convergence properties, as follows: [13], [14]

1) Velocity alignment:

$$\lim_{t\to\infty} |v_i(t) - v_j(t)| = 0, \quad \text{for } \forall i \neq j. \tag{7}$$

2) Formation of a group:

$$\sup_{0\le t<\infty} |x_i(t) - x_j(t)| < \infty, \quad \text{for } \forall i \neq j. \tag{8}$$

Then, why do birds flock together? There are a variety of reasons, such as foraging, mating, navigation, protection from predators, etc. Among them, one theory is that in coordinated flight of birds, there is an aerodynamic advantage to flying behind [15]. As a front bird moves its wings up and down, a strong current of air is created and flows backward. This moving wave of air uplifts the bird behind it. That is, each bird flying ahead creates an air wave that helps the bird flying behind it. This cooperation reduces the energy consumption of birds and thus allows them to arrive faster at their destination [16]. Because of these aerodynamic interactions, the best way for a bird group to arrive at the destination as soon as possible without straggling (i.e., to maximize the minimum bird speed) is to cooperate with each other in a way that the speedy birds fly in front of the tardy birds. As a result, this cooperation makes all birds fly at the same velocity. Therefore, it is noticed that the flocking algorithm equalizing all the birds' velocity can be an appropriate solution to achieve the goal of bird flock.

IV. Proposed Bio-Inspired Transmit Power Control Algorithm

Both the multi-hop transmission and the flocking behavior have the objective function of the max-min type. Moreover, the flocking algorithm is a basically simple and distributed approach and has the convergence properties. Considering these similarity and advantages, we adapt the flocking algorithm to the TPC algorithm for the wireless multi-hop transmission.

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Similar to the flocking algorithm, we equalize the link rates by adjusting the transmit power of each node. That is to say, the proposed BiTPC algorithm controls the transmit power of each node in such a way to equalize all the link rates (i.e., $R_{12} = R_{23} = \cdots = R_{n(n+1)}$). Because the rate of link ij, R_{ij}, is related to the transmit powers of all the other nodes ($P_k, \forall k \neq i, j$) as well as to the transmit power of node i (P_i), the control of one node's transmit power influences all the other nodes' rates, and this requires an iteration to obtain the final equal rate value. At each step, each node recognizes the rate value of its neighboring nodes and uses the average of the recognized rate values as its next target rate, as each bird in the flock matches its velocity with its neighboring birds repeatedly in a distributed manner. Thereafter, each transmitting node decides the transmit power to achieve the target rate individually. This distributed local rate-average operation is repeated until all the link rates converge to the same value.

The flow chart of the proposed BiTPC algorithm is shown in Fig. 2, and its detailed operation follows these steps:

1) All the transmitting nodes set the initial transmit power to the maximum transmit power P_{max}.
2) The transmitting node i sends the packet to its receiving node j by using the transmit power $P_i(t)$ decided for time t.
3) Upon receiving the packet, the receiving node j measures its SINR$_{ij}$ and feeds it back to its transmitting node i.
4) On the basis of the SINR feedback, the transmitting node i calculates its current link rate as $R_{ij}(t) = \log_2(1 + \text{SINR}_{ij}(t))$.
5) Each transmitting node shares the information of $R_{ij}(t)$ or SINR$_{ij}(t)$ with its neighboring nodes. Note that the rate and SINR can be converted to each other. As a candidate sharing method, the overhearing technique is possible [17]. With this technique, the node overhears the SINR feedback or the transmitted modulation and coding set (MCS) information of the adjacent nodes; therefore, these information of adjacent links can be shared among nodes without additional signalling for sharing.
6) The next target rate $R_{ij}(t+1)$ is determined as the average value of the recognized adjacent link rates, as follows:

$$R_{ij}(t+1) - R_{ij}(t) = \frac{1}{\eta} \sum_{\forall k, l=k+1} \psi(|x_k - x_i|)\,(R_{kl}(t) - R_{ij}(t)) \quad (9)$$

$$\Rightarrow R_{ij}(t+1) = \frac{1}{\eta} \sum_{kl \in \{\text{neighbor links}\}} R_{kl}(t) \quad (10)$$

where η is the total number of neighbor links whose rate information is shared. The communication range function $\psi(|x_k - x_i|) = 1$ if the node k is the neighbor of the node i and the node k's rate information is shared. Otherwise, $\psi(|x_k - x_i|) = 0$.
7) If the next target rate $R_{ij}(t+1)$ has little difference with the current target rate $R_{ij}(t)$ (i.e., $R_{ij}(t+1) - R_{ij}(t) \leq \epsilon$ where $\epsilon > 0$ is small enough), $P_i(t)$ is determined to be the final transmit power and the iteration ends. Otherwise, from (4) and (5), the next transmit power $P_i(t+1)$ is calculated to obtain the next target rate $R_{ij}(t+1)$, as follows:

$$P_i(t{+}1) = \min\left[\frac{\{2^{R_{ij}(t+1)} - 1\}\{I_j(t) + N_j(t)\}}{g_{ij}}, P_{max}\right] \quad (11)$$

where $\frac{I_j(t)+N_j(t)}{g_{ij}}$ can be derived from the SINR$_{ij}(t)$ feedback. Thereafter, the operation continues at Step 2.

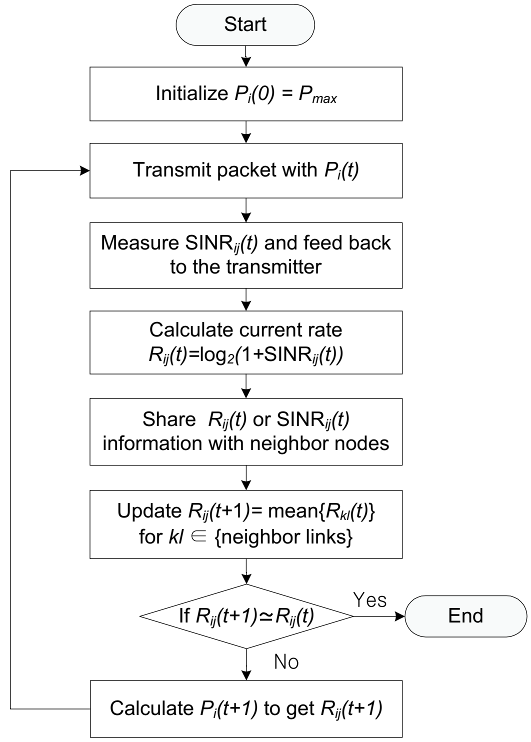

Figure 2. Flow chart of proposed BiTPC algorithm.

V. PROOF OF OPTIMALITY

The rate set of wireless links that use the same radio resource at the same time affect each other owing to their mutual interference [18]. Therefore, as expressed in (4), it is always possible to increase the rate of one link at the expense of another. We call this property *solidarity* and define it as follow.

Definition 1 (Solidarity Property): A subset $\mathcal{X}$ of $\mathbb{R}^n$ has a solidarity property if and only if for all $i \in \{1, 2, \cdots, n\}$, for all $\mathbf{x} \in \mathcal{X}$ where the i-th element $\mathrm{x}_i > 0$, and for all $0 < \alpha_i < \epsilon$ where $\epsilon > 0$ is small enough, the variation of x_i, $\mathrm{x}_i \pm \alpha_i$, induces variations of the other elements, $\mathrm{x}_j \mp \alpha_j$ for $\forall j \neq i$ and $0 < \alpha_j < \epsilon$, and the changed vector $\mathbf{y} = \mathbf{x} \pm \alpha_i \mathbf{e}_i \mp \sum_{\forall j \neq i} \alpha_j \mathbf{e}_j$ where $\mathbf{e}_i$ is a unit vector still belongs to $\mathcal{X}$.

According to the definition of the solidarity property, we state the following proposition and prove it in order to verify that the proposed BiTPC algorithm is an optimal solution to maximize the end-to-end rate of the wireless multi-hop link.

Proposition 1: If a set $\mathcal{X}$ has the solidarity property, then the *max-min fair* vector $\mathbf{x} \in \mathcal{X}$ has all components equal,

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TABLE I. SIMULATION PARAMETERS

Parameter	Value
Distance btw. source and destination	1000 m
Minimum distance between nodes	10 m
Number of transmission hops	1∼15
Information-sharing range	2 hops (default)
Maximum transmit power	23 dBm
Distance-dependent path loss	128.1+37.6$\log_{10}R$ [dB], R in km
Noise figure	9 dB
Threshold for convergence check	10^{-2}

that is, $x_i = x_j$ for $\forall i, j$ when the minimum value of $\mathbf{x}$ is maximized.

Proof: Suppose the contrary that there exists a max-min fair vector $\mathbf{x}$, such that $x_i \neq x_j$ for some $i \neq j$ on $\mathcal{X}$ with the solidarity property. Let x_i be the largest component of $\mathbf{x}$. Then, for sufficiently small ϵ such that $0 < \epsilon < \min_j\{x_i - x_j\}$, we have

$$x_i > x_j + \epsilon \quad \text{for } \forall j \neq i. \tag{12}$$

According to the definition of the solidarity property, for $0 < \alpha_i, \alpha_j < \epsilon$, we can find another vector $\mathbf{y} \in \mathcal{X}$ such that

$$\mathbf{y} = \mathbf{x} - \alpha_i \mathbf{e}_i + \sum_{\forall j \neq i} \alpha_j \mathbf{e}_j. \tag{13}$$

That is, $y_i = x_i - \alpha_i$ and $y_j = x_j + \alpha_j$ for $\forall j \neq i$. This satisfies $y_i > x_i - \epsilon > x_j$ and $y_j > x_j$ for $\forall j \neq i$. Therefore, all elements of $\mathbf{y}$ are greater than x_j, i.e.,

$$\max\{\min(\mathbf{y})\} > \max\{\min(\mathbf{x})\} = x_j \tag{14}$$

which contradicts the supposition that $\mathbf{x}$ is the max-min fair vector. ■

The rate set of links consisting of the wireless multi-hop link has the solidarity property. Moreover, the multi-hop end-to-end rate is determined by the minimum link rate. Consequently, from Proposition 1, the multi-hop end-to-end rate is maximized when all the link rates are equal. Therefore, the proposed BiTPC algorithm, which controls the transmit power of each node in such a way as to equalize all the link rates, maximizes the end-to-end rate of the multi-hop link.

VI. RESULTS AND DISCUSSION

We consider a one-way linear multi-hop wireless network, as shown in Fig. 1. Table I shows the simulation parameters. The distance between the source node and the destination node is fixed as 1000 m and the number of transmission hops is varied by controlling the number of relay nodes between them. The relay node is deployed randomly on the line connecting the source node with the destination node, and the requirement of the minimum distance between the nodes is 10 m. The default information-sharing range is 2 hops, within which the nodes can share their rate or the SINR value. The maximum power is set to 23 dBm and the path loss follows the 3GPP evaluation parameter [19]. For comparison, we consider a scheme using the maximum equal power without TPC and the SINR-based TPC algorithm with several target SINR values [3]-[5].

Fig. 3 shows the rate of each link and the transmit power of each node according to the iteration of the proposed algorithm at one topology. Here, we assume that the iteration process is stopped if the Euclidean length of a transmission power

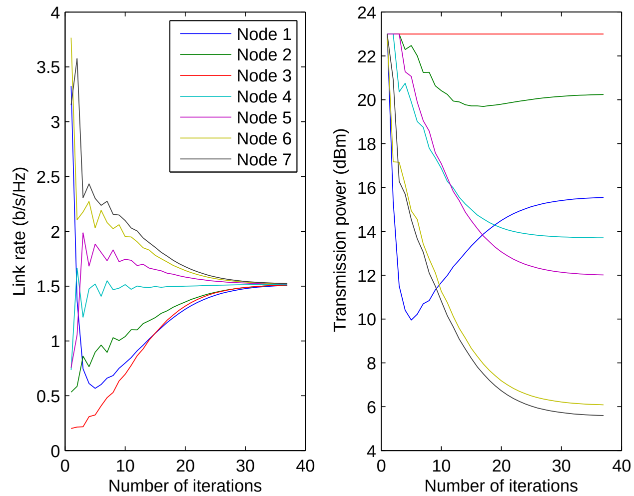

Figure 3. Link rate and transmission power vs. number of iterations.

vector $\mathbf{P}$ (i.e., norm of $\mathbf{P}$) is less than 10^{-2}. Note that this convergence check corresponds to a tight condition because in practical systems, set of possible bit rate is determined by several MCS levels. Therefore, the convergence speed can be improved further by relaxing the convergence condition especially in case that the channel variation and node mobility become more dynamic. As the iteration proceeds, the link rates converge, but the transmit powers become different and bounded. From the perspective of convergence, the simulation results have showed that $\lim_{t\to\infty} |R_i(t) - R_j(t)| = 0$ for $\forall i \neq j$ and $\sup_{0\leq t<\infty} |P_i(t) - P_j(t)| < P_{max}$ for $\forall i \neq j$. This is caused by the fact that the proposed BiTPC algorithm limits the maximum transmission power. Accordingly, the BiTPC algorithm shows the similar convergence properties to the flocking algorithm, as shown in (7) and (8).

Upon convergence, the node that initially had the best link rate (i.e., node 7) shows the lowest transmit power, and the node that initially had the worst link rate (i.e., node 3) maintains the maximum transmit power. That is, the nodes with good link quality reduce their transmit power, but the nodes with bad link quality maintain or slightly reduce their transmit power, in order to equalize all link rates. It should be noted that the final transmit power is inversely proportional to the initial link rate.

Fig. 4 shows the number of iterations needed for convergence, according to the number of transmission hops and the number of sharing hops. As the number of hops increases, the number of iterations increases exponentially because an increase in the number of nodes means that more time is required to equalize all the link rates. Moreover, as the number of sharing hops increases, the convergence becomes faster. This is because the increase in the number of sharing hops offers more adjacent link rates for averaging.

Fig. 5 shows the performance of the multi-hop end-to-end rate versus the number of transmission hops. The proposed BiTPC algorithm outperforms the scheme using the maximum equal power without TPC and the SINR-based TPC with a target SINR (γ) fixed at 0, 3, or 10 dBm. This is because

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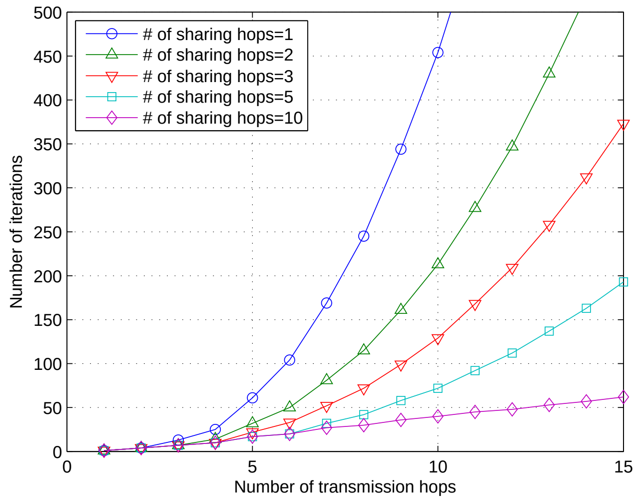

Figure 4. Number of iterations vs. number of hops and number of sharing hops.

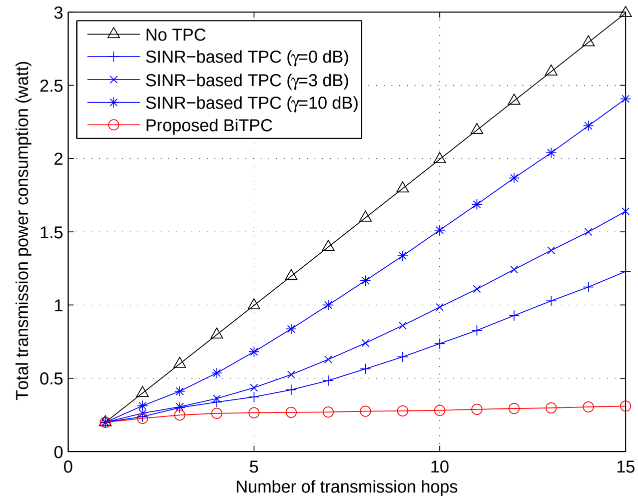

Figure 6. Total transmission power vs. number of hops.

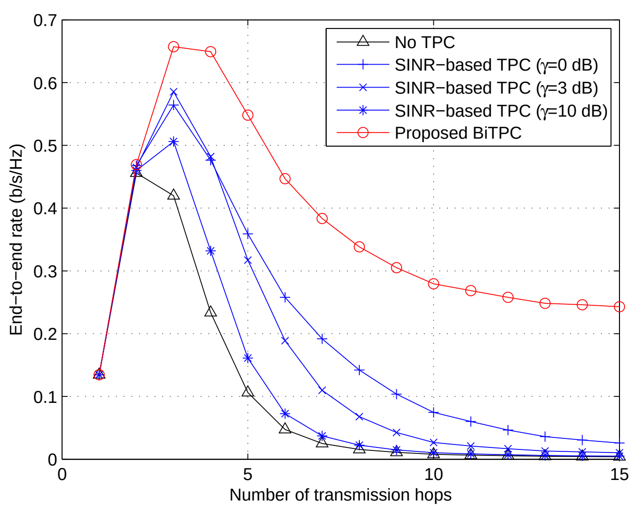

Figure 5. End-to-end rate vs. number of hops.

the proposed TPC algorithm dynamically achieves a SINR value that maximizes the end-to-end throughput, while the SINR-based TPC algorithm achieves a static target SINR. As the number of hops increases, the end-to-end rate increases sharply, but eventually decreases and maintains a constant level in both schemes. The increase in the number of hops initially improves the link budget and thus enhances the end-to-end rate, but the excessive number of hops causes more interference and degrades the end-to-end rate. This implies that not only the optimal TPC but also the optimal selection of transmission hops is required for maximizing the end-to-end rate in the given multi-hop environment.

Fig. 6 shows the performance of total transmission power consumption of all the transmitting nodes (i.e., the sum of the transmission power of each node) versus the number of transmission hops. The scheme without TPC uses a fixed maximum transmit power in all the nodes, so the total power consumption increases linearly according to the number of hops. On the other hand, the SINR-based and the proposed TPC algorithms use decreased transmission power. Particularly, the proposed BiTPC reduces the transmit power adaptively depending on the increase of interference due to the increased number of hops, and therefore, it exhibits very low power consumption. Note that the SINR-based TPC shows a tradeoff in performance between the end-to-end throughput and the total transmission power consumption according to the target SINR value.

VII. CONCLUSION

Inspired by the flocking algorithm, we proposed the BiTPC algorithm, which determines the transmit powers of nodes that equalize all the link rates on the multi-hop path. We proved that this rate-averaging algorithm is an optimal solution to maximize the multi-hop end-to-end rate in wireless networks with the solidarity property. The simulation results showed that the proposed BiTPC algorithm has the converged performances, regardless of the number of transmission hops and the information-sharing range, and leads to significant energy savings at the transmitting nodes by adjusting the transmit powers. Since the BiTPC algorithm is basically simple, distributed, and optimal, we expect that it will be practically used in complex and unstructured network environments. For further study, we will extend the basic concept of our BiTPC algorithm in the linear topology to the environment where multi-flow exists in the two-dimensional multi-hop topology.

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