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A Joint Solution to Scheduling and Power Control for Multicasting in Wireless Ad Hoc Networks

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This paper jointly addresses the problem of power control and scheduling in ad hoc networks supporting multicast traffic. First, we present a distributed algorithm which, given the set of multicast transmitters and their corresponding receivers, provides an optimal solution to the power control problem, if there is any. The transmit power levels obtained by solving the optimization problem minimize the network power expenditure while meeting the requirements on the SINR at the receivers. Whenever no optimal solution can be found for the given set of multicast transmitters, we introduce a joint scheduling and power control algorithm which eliminates the strong interferers, thus allowing the other transmitters to solve the power control problem. The algorithm can be implemented in a distributed manner. Although the proposed scheme provides a suboptimal solution, simulation results show that the obtained solution is close to the global optimum, when it exists. When instead there is no optimal solution, our algorithm allows for a high number of successful multicast transmissions.

Keywords and phrases: wireless ad hoc networks, scheduling, power control, multicasting.

1. INTRODUCTION

Multicasting enables data delivery to multiple recipients in a more efficient manner than traditional unicasting and broadcasting. A packet is duplicated only when the delivery path toward the traffic destinations diverges at a node, thus helping to reduce unnecessary transmissions. Therefore, in wireless ad hoc networks, where radio resources are scarce and most devices rely on limited energy supply, multicasting is a highly desirable feature.

In this paper, we jointly address the problem of power control and scheduling in ad hoc networks supporting multicast traffic. Power control is a fundamental issue since (i) it reduces the nodes' power consumption and (ii) it increases the number of successful simultaneous transmissions by decreasing multiuser interference. The problem of power control in wireless networks has been widely studied in the context of both cellular and ad hoc networks. The power control algorithms in [1, 2, 3, 4, 5] are designed for a cellular environment but they apply to the case of unicast transmissions in ad hoc networks as well. In particular, in [5] a simple distributed algorithm is introduced, which maximizes the signal-to-interference-and-noise ratio (SINR) at any receivers while minimizing the total transmission power [3]. The problem of optimally controlling the node transmission range in ad hoc networks is addressed in [6, 7]. In [8], the authors employ power control to adjust the node power level so as to create a desired network topology. In [9], power control is used within the *carrier-sense multiple access with collision-avoidance* (CSMA/CA) MAC scheme to improve spatial channel reuse. The method proposed there applies specifically to CSMA/CA-based systems, and does not guarantee that the allocated transmission power levels are minimum.

With regard to scheduling and admission control in wireless networks, several proposals have appeared in the literature. In the context of ad hoc networks, a scheduling scheme which provides fairness in channel access and maximizes spatial reuse of bandwidth is presented in [10]. Admission control and power control aspects are addressed in [11], where the authors present a distributed scheme which maintains the SIR of active radio links above their required thresholds while new users require for admission into the system. The distributed power control problem for multicast traffic in a cellular environment is first addressed in [12, 13]. There, based on appropriate criteria, the base stations remove multicast connections via an iterative procedure, until the target outage probability is met. We highlight that the algorithm in [12, 13] uses the approach presented in [5], hence it requires iterations. Our work instead is based on flow control, and the distributed joint scheduling and power control algorithm that we propose does not require iterations.

The work closest to ours is the joint scheduling and power control scheme for ad hoc networks that has been presented in [14]. There, the key idea is that strong interferers are eliminated so that the remaining nodes can solve the power control problem by using the algorithm in [5]. The scheduling scheme proposed in [14] is designed for unicast transmissions and does not apply to multicasting; furthermore, it assumes the existence of a central scheduler and that each node knows the geographical position of all other nodes. Our work differs from [14] in dealing with a multicast traffic scenario and in proposing a distributed algorithm.

We start by focusing on power control. We consider a given set of multicast transmitters and their corresponding receivers. Our goal is to determine the optimal values of transmit power so that the requirements on the SINR at the receivers are fulfilled while the total power expenditure is minimized. We describe the system model and the formulation of the power control problem in Section 2, while, in Section 3, we present a distributed algorithm that yields the optimum solution. Next, in Section 4, we consider the situation where, given the set of multicast transmitters and receivers, the optimization problem does not have a solution. As in the case of unicast transmissions addressed in [14], we need a joint scheduling and power control algorithm which eliminates the strong interferers and allows the remaining nodes to solve the power control problem. The joint scheme that we propose is able to deal with one-to-many transmissions and can be implemented in a distributed manner. However, since it uses "local" information, it gives a suboptimal solution. In Section 5, we show through simulations that the values of transmit power obtained by using the proposed algorithm are close to the optimum, when it exists. When there is no optimal solution, the presented results show that our scheme enables a high number of nodes to successfully transmit multicast traffic. We point out that, in this case, the scheduling would be suboptimal even if every node had global information; indeed, the optimal scheduling that selects the maximum number of successful simultaneous connections is one of the classic NP-hard problems in graph theory [15].

2. AN LP FORMULATION OF THE POWER CONTROL PROBLEM FOR MULTICASTING

We consider an ad hoc network composed of stationary nodes, each of them equipped with an omnidirectional antenna. Nodes access the channel by using a TDMA/CDMA scheme with a fixed time-slot duration, which accounts for the packet transmission time and a guard time interval. Links between any pair of nodes are assumed to be bidirectional.

We focus on the case of multicast traffic connections. We assume that for each traffic connection, the multicast tree has been already constructed and there is no conflict in the transmission setup, that is, each receiver is associated with only one transmitter at a time. We are not concerned with traffic routing from the multicast source to the destination. Rather, we focus on next neighbor transmissions, that is, sending packet traffic to the specified neighbors while meeting constraints on the SINR at the intended receivers [14].

We consider a set of transmitters, denoted by $\mathcal{S}$, and a set of receivers, denoted by $\mathcal{R}$. S and R indicate the number of transmitters and receivers, respectively. Since we deal with multicasting, we have that $S \leq R$; that is, each transmitter sends data packets to at least one receiver. We define P_k^t as the transmission power of the generic node k, and assume that a node cannot transmit at a power level higher than $P_{\max}$, that is, $0 \leq P_k^t \leq P_{\max}$. Every transmitter causes interference to any receivers, and the amount of interference depends on the propagation attenuation of the transmitted signal. We assume that the signal attenuation over the radio channel is either constant or slowly changing, and that the receivers notify their propagation attenuation measurements to the associated transmitter. Feedback information is encoded with a strong error correction code so that they are always correctly received by the destination nodes.

We assume that interference caused by simultaneous transmissions is treated as noise. Let $s(i)$ denote the node sending a packet to receiver node i. Node i receives a transmission from $s(i)$ successfully if the corresponding SINR at node i is equal to or greater than a given threshold γ_i, that is,

$$\frac{a_{s(i)i}P_{s(i)}^t}{\sigma_n^2 + (1/L)\sum_{k\neq s(i)} a_{ki}P_k^t} \geq \gamma_i, \tag{1}$$

where a_{ki} is the propagation attenuation of the signal from transmitter k to receiver i, σ_n^2 is the noise power spectrum density, and L is the system processing gain.

Our first goal is to have the expression in (1) satisfied for all of the nodes in $\mathcal{R}$. Thus, by defining $\vec{\gamma} = \sigma_n^2[\gamma_1, \dots, \gamma_R]^T$ and $\vec{P^t} = [P_1^t, \dots, P_S^t]^T$, we must have

$$\mathbf{A}\vec{P^t} \geq \vec{\gamma}, \tag{2}$$

where $\mathbf{A}$ is an $R \times S$ matrix given by

$$\mathbf{A} = \begin{bmatrix} -\frac{\gamma_1}{L}a_{11} & \cdots & \cdots & a_{s(1)1} & \cdots & -\frac{\gamma_1}{L}a_{S1} \\ -\frac{\gamma_2}{L}a_{12} & a_{s(2)2} & \cdots & \cdots & \cdots & -\frac{\gamma_2}{L}a_{S2} \\ \vdots & \vdots & & & \vdots & \vdots \\ -\frac{\gamma_R}{L}a_{1R} & \cdots & a_{s(R)R} & \cdots & \cdots & -\frac{\gamma_R}{L}a_{SR} \end{bmatrix}. \quad (3)$$

Notice that, for each row of $\mathbf{A}$, that is, for each receiver in $\mathcal{R}$, there is only one positive entry which corresponds to the signal received from the intended sender. All other elements are negative and account for the interfering transmissions.

Our second goal is to minimize the total transmission power. To this end, we formulate the following linear programming (LP) problem:

$$\mathbf{P} : \text{minimize} \quad \sum_{k=1}^{S} P_k^t \quad (4)$$

$$\begin{aligned} \text{subject to} \quad & \mathbf{A}\vec{P^t} \geq \vec{\gamma}, \\ & 0 \leq P_k^t \leq P_{\max} \quad \text{for } 1 \leq k \leq S. \end{aligned} \quad (5)$$

If a solution to problem $\mathbf{P}$ exists, this provides the optimal transmission power vector such that the total power expenditure of the system is minimized. By using the following theorem, we prove that, if there is a transmit power vector P^t which satisfies constraints (5), then a solution to problem $\mathbf{P}$ exists.

Theorem 1. *An optimal solution to problem* $\mathbf{P}$ *exists if and only if there is a solution to* (5)*, that is, there is at least one set of transmission powers which ensures the successful reception at all of the receiver nodes.*

Proof. The converse is obvious. In order to show that an optimal solution to problem $\mathbf{P}$ exists if there is a solution to (5), we note that the values of transmit power are bounded, since $0 \leq P_k^t \leq P_{\max}$, $k = 1, \ldots, S$. Hence, an optimal solution to the LP problem exists by virtue of [16, Theorem 3.4]. □

3. AN OPTIMAL DISTRIBUTED SOLUTION TO POWER CONTROL FOR MULTICASTING

In this section, we present a distributed solution to the optimization problem $\mathbf{P}$.

We draw upon previous work on flow control. In particular, we consider the approach used in [17], where the transmission rates of traffic sources are derived as a solution of an optimization problem. Each traffic source is associated with a *utility function* increasing in its transmission rate and subject to bandwidth constraints. The network objective there is to maximize the sum of source utilities. The problem is decomposed into several subproblems each of which corresponds to a single traffic source. It is shown that, when the objective function is strictly concave, the solution to the original problem can be obtained by solving the single source subproblems. The key of the approach presented in [17] is to use a dual formulation of the problem.

In our case, we start out by considering the following primal problem $\mathbf{P}'$:

$$\begin{aligned} \mathbf{P}' : \max_{\vec{P^t}} & \sum_{k=1}^{S} f(P_k^t) \\ \text{subject to} \quad & \mathbf{A}\vec{P^t} \geq \vec{\gamma}, \\ & 0 \leq P_k^t \leq P_{\max} \quad \text{for } 1 \leq k \leq S, \end{aligned} \quad (6)$$

with $f(P_k^t)$ having the following properties: (i) it is a twice continuously differentiable, strictly concave function, (ii) it decreases with the increase of P_k^t, and (iii) it is such that $f''(0) < 0$. The term $\sum f(P_k^t)$ captures the idea that increasing the transmit power is not beneficial to the network system since it leads to higher energy consumption as well as interference to neighboring transmitters. Clearly, solving problem $\mathbf{P}'$ maximizes $\sum f(P_k^t)$, while our goal is to minimize the total transmit power, that is, maximize $\sum -P_k^t$. However, later in this section, we will show that maximizing $\sum f(P_k^t)$ is equivalent to maximizing $\sum -P_k^t$.

We define

$$\begin{aligned} D(\vec{c}) &= \max_{\vec{P^t}} \sum_{k=1}^{S} f(P_k^t) + \vec{c}^T \left(\mathbf{A}\vec{P^t} - \vec{\gamma}\right) \\ &= \max_{\vec{P^t}} \sum_{k=1}^{S} \left[f(P_k^t) + \left(\vec{c}^T \mathbf{A}\right)_k P_k^t \right] - \vec{c}^T \vec{\gamma}, \end{aligned} \quad (7)$$

where $\vec{c} = [c_1, \ldots, c_R]^T$ with $c_k \geq 0$ being the cost that the kth receiver charges for all of the transmitters, and the notation $(\vec{v})_k$ denotes the kth element of a generic vector $\vec{v}$. The term $\vec{c}^T(\mathbf{A}\vec{P^t} - \vec{\gamma})$ accounts for the fact that the transmission power should be sufficiently large so that the target SINR is met at every receiver.

Then, we formulate the dual problem as follows:

$$\mathbf{D}' : \min_{\vec{c}} D(\vec{c}). \quad (8)$$

In general, the solution $\vec{P^t}$ that is obtained by solving $\mathbf{D}'$ for an arbitrary $\vec{c}$ is not primal optimal. However, according to the dual theory, there exists a dual optimal cost vector $\vec{c}^*$ such that $\vec{P^t}^*$ is primal optimal [17]. Given $\vec{c}^*$, the first term in (7) is separable in P^t, so we can decompose the maximization problem into S subproblems as follows:

$$\begin{aligned} &\max_{\vec{P^t}} \sum_{k=1}^{S} f(P_k^t) + \left(\vec{c}^T \mathbf{A}\right)_k P_k^t \\ &\quad = \sum_{k=1}^{S} \max_{P_k^t} \left\{ f(P_k^t) + \left(\vec{c}^T \mathbf{A}\right)_k P_k^t \right\}. \end{aligned} \quad (9)$$

The solution to the kth transmitter's subproblem is given by [17]

$$P_k^t = f'^{-1}\Big(-\big(\vec{c}^T\mathbf{A}\big)_k\Big), \quad k = 1,\ldots,S, \tag{10}$$

where f'^{-1} is the inverse of the derivative of f. The global solution to problem $\mathbf{D}'$ is obtained by combining the solutions to the single-transmitter subproblems.

In [17], a distributed, iterative algorithm is given which is proven to lead to the primal optimal solution, provided that the step-size parameter for the iteration is appropriately chosen. This algorithm can be applied to (7) with slight modifications. The iterative algorithm to be performed at the generic receiver i and sender k, for each multicast transmission, is reported below. We indicate with n the generic step of the iterative procedure and with $\delta > 0$ the step-size parameter [17].

Receiver's algorithm

(1) Detect the signal received from each transmitter and estimate the SINR.
(2) Compute the receiver cost as $\vec{c_i}(n) = \vec{c_i}(n-1) - \delta(\mathbf{A}\vec{P^t}(n-1) - \vec{\gamma})_i$.
(3) Send the new cost $\vec{c_i}(n)$ to all transmitters.

Transmitter's algorithm

(1) Receive the costs from the receivers.
(2) Compute the new transmit power level P_k^t by substituting $\vec{c}(n)$ into (10).
(3) Transmit a packet by using the new value of P_k^t.

Remarks

(i) Observe that receiver i increases its cost if it finds out that its SINR threshold has not been met. Assuming that all other receivers do not vary their costs, this leads the transmitter associated with i to increase its transmit power, and the interfering transmitters to lower their power. In fact, f'^{-1} is a decreasing function and the elements in matrix $\mathbf{A}$ are positive for the intended transmitters and negative for the interfering ones.

(ii) If we assume that a sender reaches only the nodes that are within its transmission range, we can consider that a transmitter causes interference only to the receivers in its proximity, and thus we can neglect small elements in $\mathbf{A}$. This would also imply that a receiver needs to feedback the cost information just to the senders in its proximity.

Next, we show that when the algorithm converges to an optimum solution $\vec{P^t}^*$, this maximizes $\sum f(P_i^t)$ as well as $\sum -P_k^t$. Whenever a feasible solution exists, it is well known that there exists a Pareto optimal solution to the unicast version of problem $\mathbf{P}$ [3], that is, $\vec{P^t}^* \le \vec{P^t}$ for any other $\vec{P^t}$ such that $\mathbf{A}\vec{P^t} \ge \vec{\gamma}$. For the multicast case, $\mathbf{A}$ is no longer a square matrix. However, through the theorem below, we will show that the problem can be converted to the unicast version.

Theorem 2. *For the multicasting problem defined above, if the inequality $\mathbf{A}\vec{P^t} \ge \vec{\gamma}$ has a feasible solution (i.e., there is a transmit power vector which can guarantee the target SINRs at all the receivers), then there is a unique maximizer $\vec{P^t}^*$ such that*

(i) *it satisfies $\mathbf{A}\vec{P^t}^* \ge \vec{\gamma}$,*
(ii) *it maximizes $\sum f(P_k^t)$ for any strictly decreasing function f.*

Proof. Denote the set of receivers for sender k by $\mathcal{R}(k)$. First, we consider a power vector $\vec{P^t}^*$ which satisfies $\mathbf{A}\vec{P^t}^* \ge \vec{\gamma}$ and maximizes $\sum f(P_k^t)$ for a (not any) strictly decreasing function f. We prove that, given $\vec{P^t}^*$, for each sender k, there is at least one receiver in $\mathcal{R}(k)$ whose SINR is exactly equal to its target SINR. That is, by denoting such a receiver by $r(k)$, we have $(\mathbf{A}\vec{P^t}^*)_{r(k)} = \gamma_{r(k)}$.

We prove this by contradiction. Suppose there exists a sender k such that all receivers in $\mathcal{R}(k)$ exceed their target SINR. We can reduce P_k^{t*} by a certain amount and leave the transmit power of the other nodes unchanged, so that at least one receiver in $\mathcal{R}(k)$ reaches exactly its target SINR while the other receivers still exceed theirs. Observe that, since the interference from transmitter k is reduced, the SINRs at all the other receivers are still met. Moreover, f being strictly decreasing, the new power vector P^t increases $\sum f(P_k^t)$, which contradicts the assumption that $\vec{P^t}^*$ is a maximizer.

Now, we consider an $S \times S$ square matrix $\mathbf{A}'$ created by taking for every sender k, $k \in \mathcal{S}$, the $r(k)$th row of $\mathbf{A}$. Also, consider an $S \times 1$ vector $\vec{\gamma}'$ created by taking the $r(k)$th element of $\vec{\gamma}$ for $1 \le k \le S$. This is equivalent to considering the unicast transmission problem, for which we have $\mathbf{A}'\vec{P^t}^* = \vec{\gamma}'$. In such a case, $\mathbf{A}'$ is a full-rank matrix if there exists a feasible power vector [18]. If so, we can write $\vec{P}^* = (\mathbf{A}')^{-1}\vec{\gamma}'$. For any feasible $\vec{P}$, it must satisfy $\mathbf{A}'\vec{P} \ge \vec{\gamma}'$, and therefore $\vec{P} \ge \vec{P}^*$ [18].

This result shows that the optimal solution $\vec{P}^*$ is Pareto optimal for the multicast case too, that is, $\vec{P}^* \le \vec{P}$ for any other $\vec{P}$ such that $\mathbf{A}\vec{P} \ge \vec{\gamma}$.

By using the result proved above, we conclude that $\vec{P^t}^*$ satisfies $\mathbf{A}\vec{P^t}^* \ge \vec{\gamma}$, is unique, and maximizes $\sum f(P_k^t)$ for *any* strictly decreasing function f. □

To summarize, in this section, we presented a distributed power control algorithm which, whenever a solution to problem $\mathbf{P}$ exists, converges to the optimum power vector, thus minimizing the total transmission power.[1]

However, there are many situations where the power control problem $\mathbf{P}$ has no solution. In such cases, not all nodes in $\mathcal{S}$ should be allowed to transmit [14]. In the next section, we propose a scheduling algorithm that eliminates the strongest

[1]Note that any function $f(P_k^t)$ will converge to the optimal solution as long as it meets the definition given for this function earlier in the paper and the step size is appropriate.

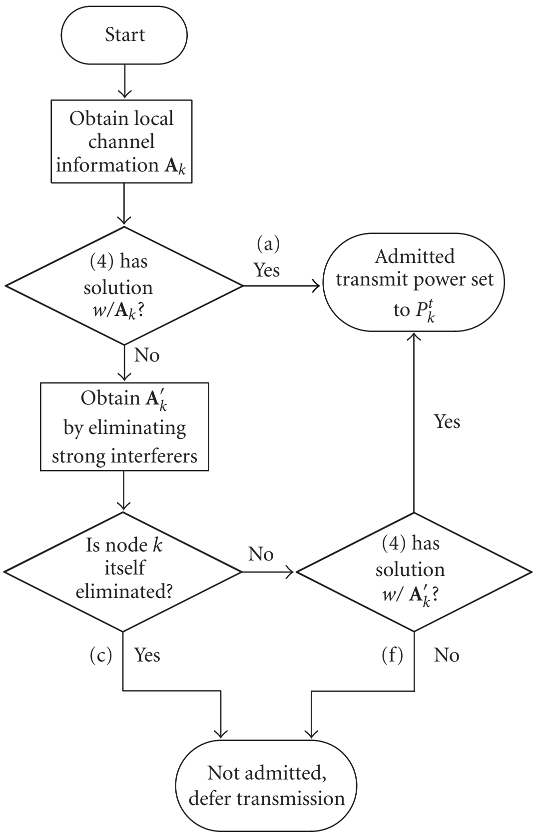


FIGURE 1: Flow chart of the joint scheduling and power control algorithm.

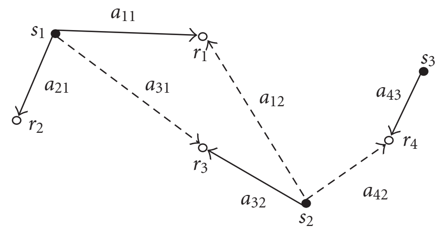


FIGURE 2: An example of a network with three multicast transmitters and four receivers. Each transmitter is connected to the intended receivers by solid lines and to the unintended receivers by dotted lines.

multicast interferers and enables the nodes entitled to transmit to solve the power control problem.

4. A DISTRIBUTED JOINT SCHEDULING AND POWER CONTROL ALGORITHM FOR MULTICASTING

Here, we present a distributed scheduling scheme that enables the candidate senders to independently determine which node is allowed to transmit. While the eliminated nodes defer their transmissions, the entitled senders independently calculate their transmit power level by using a distributed power control algorithm. Such an algorithm aims at meeting the SINR requirements at any receivers while minimizing the total power consumption. We want to point out that, unlike the distributed algorithm presented in the previous section which converges to an optimal solution, the distributed joint scheduling and power control algorithm described here provides a suboptimal solution.

The joint scheduling and power control algorithm is described in detail below, and is summarized in the flow chart shown in Figure 1.

(1) Each node in $\mathcal{S}$ sends a test packet with power equal to $P_{\max}$.

(2) Each receiver detects the test packets from all transmit nodes nearby and estimates the corresponding channel attenuation. The receiver then sends a packet including all the estimated attenuation factors. As an example, consider the network shown in Figure 2, where transmitters are connected to the intended receivers by solid lines and to the unintended receivers by dotted lines. In this case, receiver r_3 estimates factors a_{31} and a_{32} and then broadcasts this information to s_1 and s_2.

(3) The generic node k, $k \in \mathcal{S}$, detects the packets from the receivers within its transmission range. From each of these receivers, k obtains the list of all possible interfering transmitters and their attenuation factors toward the receiver. Looking at Figure 2, we have that transmitter s_1 gets a packet from the intended receivers r_1 and r_2, as well as from r_3; therefore, s_1 is aware also of the signal attenuation from s_2 toward r_1 and r_3.

(4) The generic node k, $k \in \mathcal{S}$, transmits a packet with power level equal to $P_{\max}$ including the attenuation factors corresponding to all the receivers in its transmission range. In the example in Figure 2, s_2 sends a packet including the channel attenuation factors related to its transmissions toward r_1, r_3, and r_4.

(5) Each receiver retransmits such a packet. Thus, every node k, $k \in \mathcal{S}$, can acquire information related to all the transmissions reaching the receivers that are within its transmission range. Referring to the example in Figure 2, at this point, s_1 knows all channel attenuation factors except the one related to the transmission from s_3 to r_4.

(6) The generic node k, $k \in \mathcal{S}$, can construct its own copy of the channel attenuation matrix $\mathbf{A}_k$. Matrix $\mathbf{A}_k$ is based on "local" information and includes the channel attenuation related to transmissions toward nearby receivers only. Hence, its dimension is expected to be small.

(7) The generic node k, $k \in \mathcal{S}$, tries to find the optimal transmit power vector by plugging $\mathbf{A}_k$ into (4) and (5) and solving the power control problem.
   (a) If there is a solution to the power control problem, node k is allowed to transmit, and its transmit power is set to P_k^t.
   (b) Else, for each transmitter j for which a row in matrix $\mathbf{A}_k$ exists, node k computes the so-called MIMSR (*maximum-interference-to-minimum-signal ratio*), which is defined as the ratio of the

maximum absolute value of negative elements in row j to the minimum positive entry in row j. The MIMSRs are compared to a preset threshold β. If $\text{MIMSR}_j > \beta$, then the jth row is eliminated from $\mathbf{A}_k$, and a new $\mathbf{A}'_k$ is obtained.

(c) If, by doing this, the row corresponding to node k is removed, k will not participate in the current round of scheduled transmissions and defers its transmission to the next round.

(d) Otherwise, node k tries to solve the power control problem again by using $\mathbf{A}'_k$.

(e) If a solution exists, node k transmits at power P^t_k.

(f) Else, it defers its transmission attempt to the next round.

Remarks

(i) Note that the information exchange performed between transmitters and receivers in the first five steps of the procedure above only requires "local" transmissions.

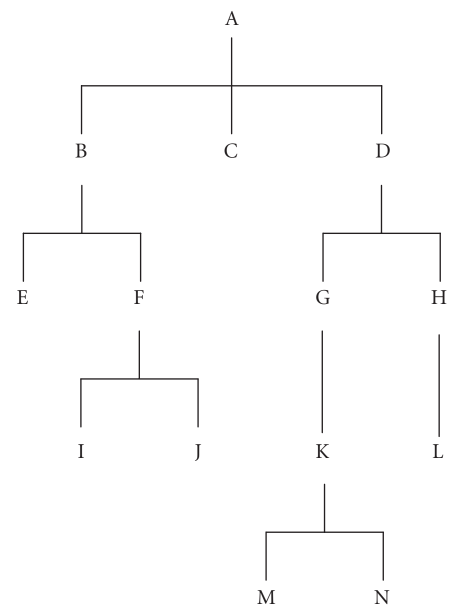
(ii) When a global solution to the optimization problem **P** exists, all nodes in $\mathcal{S}$ are allowed to transmit by the proposed scheme. However, the solution obtained through the joint scheduling and power control algorithm is suboptimal since it is based on "local" information. The more negligible the elements of **A** that do not appear in the transmitters' copies of the matrix are, the closer to the optimum the local solution is. We point out that the scheduling is suboptimal even if every node has global information. Indeed, the optimal scheduling that selects the maximum number of successful simultaneous connections is one of the classic NP-hard problems in graph theory [15].

(iii) The proposed algorithm defers the transmission of strong interferers. If everything remains the same, a strong interferer never gets the chance for transmission. This paper does not address the problem of fairness. However, it is not difficult to mitigate the fairness problem. For example, after a few attempts, a deferred source A can send out a special message to B, the source of the receiver that potentially will be severely interfered by A, and ask B to hold its transmission.

5. SIMULATION RESULTS

We derive the performance of the proposed joint scheduling and power control algorithm for a stationary network whose nodes are randomly spread over a 100×100 square region. We focus on a multicast group composed of 25 or 50 nodes, out of which one node is randomly chosen as the multicast source. We consider that the multicast tree is set up by using the MIP scheme [19]. We assume that there are two sets of senders whose transmissions alternate over time. In each odd (even) slot, transmissions are performed by the nodes in the odd (even) layer of the tree, having at least one child. The nodes, which do not transmit in a time slot, act as receivers. An example of a simple multicast tree and of the corresponding transmission scheme is presented in Figure 3.

We assume that the propagation attenuation between the generic transmitter k and receiver j is equal to $a_{kj} = 1/d^{\alpha}_{kj}$, where d_{kj} is the distance between the two nodes, and α is the power decay factor that we take to be equal to 4. The target SINR γ is set to 6 dB for any receiver, L is equal to 8, and $P_{\max}$ is equal to 5×10^7.



Sender	Receiver
A	B, C, D
F	I, J
G	K
H	L
B	E, F
D	G, H
K	M, N

Figure 3: A simple multicast tree with the associated transmission scheme.

First, we consider the case where an optimal global solution to the power control problem exists, that is, all candidate senders are allowed to transmit and hence go through step (a) in the flow chart in Figure 1. We compute the average total transmission power obtained through the distributed algorithm introduced in Section 4 and compare it to the optimal global solution. Results for $N = 50$ are presented in Figure 4. The plot shows that the suboptimal solution gives an average total transmit power that is less than the global optimal value. This is because the distributed algorithm is based on local information, and therefore the transmitters neglect some of the existing interferers while solving the power control problem. As a consequence, the percentage of receivers whose SINR is less than the target threshold in the case of the suboptimal solution will be greater than zero, whereas it is equal to zero when the optimal solution is applied.

This is shown in Figure 5, where the average percentage of receivers whose SINR is less than the target threshold is denoted by *failed transmissions* and is plotted versus the threshold β for $N = 25, 50$. The results are independent of β, as it should be, since all senders are admitted. (Recall that all

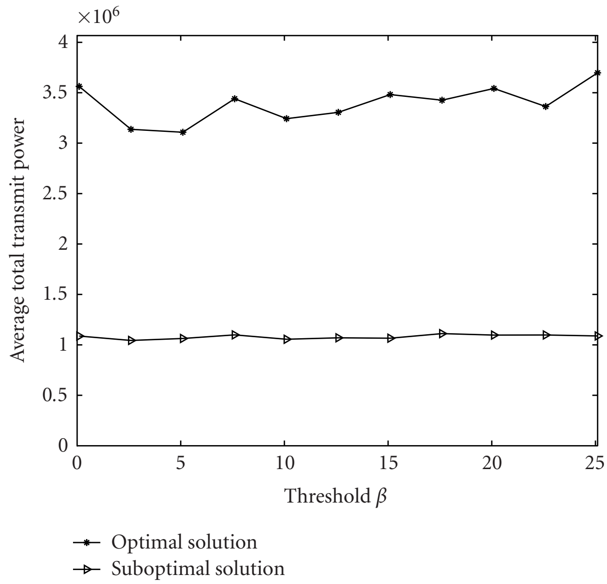


Figure 4: Comparison between the average total transmit power obtained through our distributed solution and the optimal value, as a function of β and for $N = 50$ (a case where a global solution to the power control exists).

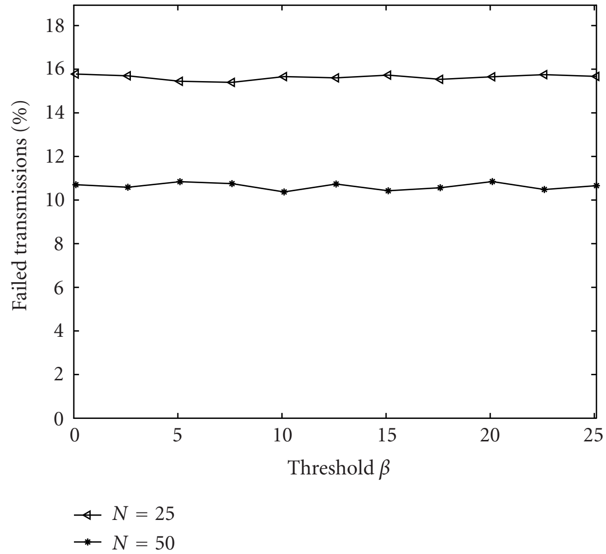


Figure 5: Average percentage of failed transmissions, that is, receivers whose SINR is less than the target threshold, as a function of β and for $N = 25, 50$ (a case where a global solution to the power control exists).

transmissions are successful when the optimal solution is applied.) Figure 5 also shows that the percentage of failed transmissions is higher for smaller values of N. Indeed, in our distributed algorithm, each sender has only local information on channel attenuation. For small values of N, there are few transmitters; thus a sender is likely to have information only on the channel attenuation between itself and its associated receivers since other transmitters are too far away. As N increases, this effect becomes less relevant and the attained transmission powers result to be closer to their optimum value.

Next, we consider the case where there is no global solution to the power control problem **P**. Figure 6 shows that the average percentage of candidate senders that are not allowed to transmit by our scheduling algorithm, as a function of the threshold β. For small values of β, the number of not admitted transmitters decreases as β increases. However, after a certain point, the number of eliminated transmitters starts increasing again with the increase of β. This is because, when β is small, many interferers are eliminated at step (c) in the flow chart in Figure 1. On the contrary, as β increases, no transmitter is eliminated at step (c), but many of the candidate senders are not allowed to transmit at step (f) since they are unable to solve problem **P**.

Figure 6 shows that the average percentage of candidate senders that are not allowed to transmit increases with N. The reason is that, as we double N, the number of receivers with which a transmission interferes increases more than twice. A sender with a large number of nonintended receivers is likely to have a large MIMSR, thus it cannot be admitted in the system. It follows that the number of not admitted nodes increases with N.

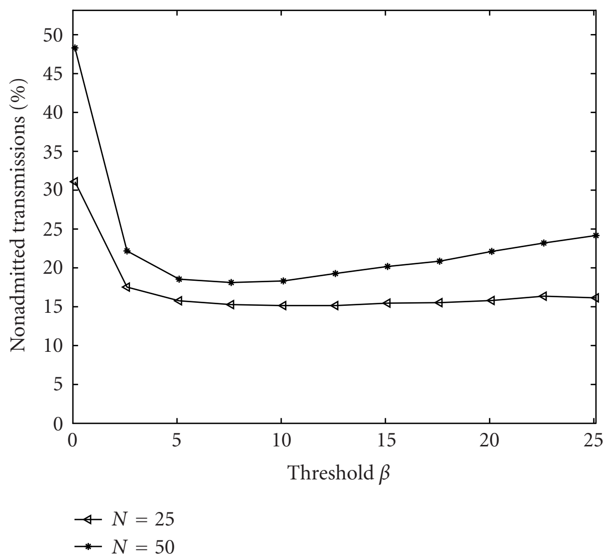


Figure 6: Average percentage of candidate senders not allowed to transmit, as a function of β and for $N = 25, 50$ (a case where no global solution to the power control exists).

Then, among the admitted transmissions, we compute the average percentage of receivers whose SINR is less than the target threshold, that is, the failed transmissions, in the case where no global solution exists. The results are plotted versus β in Figure 7. The number of failed transmissions first increases and then decreases as β grows. This is because when β is very small or very large, admitted transmissions enjoy a lower interference level with respect to the

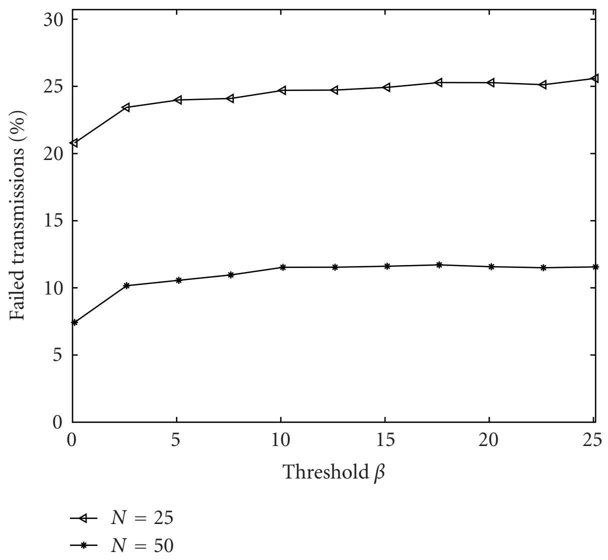


Figure 7: Average percentage of failed transmissions, that is, receivers whose SINR is less than the target threshold, as a function of β and for $N = 25, 50$ (a case where no global solution to the power control exists).

case when intermediate values of β are used. In fact, by looking at Figure 6, we can see that less transmissions are admitted for small as well as large values of β. Figure 7 also shows that the percentage of failed transmissions is higher when N is smaller. The explanation for this behavior follows the one given for the case in Figure 5.

Finally, we highlight that the results in Figures 6 and 7 suggest that an appropriate value of β can be chosen, so that the network capacity is maximized. For example, in our network scenario, a good value for β is between 5 and 10.

6. CONCLUSIONS

In this paper, we addressed the problem of power control in ad hoc networks supporting multicast traffic and showed that this problem is similar to the one in the unicast environment.

We first presented a distributed power control scheme based on flow control. Our scheme converges to the optimal solution that minimizes the network power expenditure while meeting the requirements on the SINR at the receivers if such an optimal solution exists. However, there are sets of multicast transmitters and receivers for which an optimal solution to the power control problem does not exist. Then, we introduced a distributed joint scheduling and power control algorithm that eliminates strong interferers and enables the entitled transmitters to solve the power control problem.

Simulation results show that, when an optimal solution exists, our distributed scheme allows for a high percentage of successful transmissions. When instead there is no optimal solution, the proposed algorithm enables a high number of nodes to successfully transmit multicast traffic.

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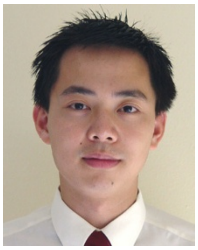

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