A Distributed Joint Scheduling and Power Control Algorithm for Multicasting in Wireless Ad Hoc Networks

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***Abstract*— This paper addresses the problem of power control 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; however, it provides a sub-optimal solution since it is based on 'local' information. Simulation results show that the obtained solution is close to the global optimum, when it exists. When there is not an optimal solution, the proposed algorithm enables us to maximize the number of successful multicast transmissions.**

I. 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 address the problem of power control in ad hoc networks supporting multicast traffic. Power control is a fundamental issue since *(i)* it reduces nodes' power consumption, and *(ii)* it increases the number of successful simultaneous transmissions by decreasing multi-user interference.

Several power control algorithms have appeared in the literature [1], [2], [3], [4], [5], [6]. Most of them have been proposed in the context of cellular radio systems, 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]. In [6], a work that is closely related to ours is presented. There, a joint scheduling and power control algorithm is proposed in the context of unicast transmissions in ad hoc networks. The scheduling algorithm eliminates strong interferers so that the remaining nodes can solve the power control problem by using the distributed algorithm in [5]. The scheme proposed in [6], however, does not apply to multicasting, and the scheduling algorithm assumes the existence of a central scheduler.

In this paper, we consider the case of multicast services in ad hoc networks, and propose a joint scheduling and power control algorithm for one-to-many transmissions, which can be implemented in a distributed manner. To the best of our knowledge such a problem has not been solved so far.

We start out by focusing on power control. We consider a given set of multicast transmitters and their corresponding receivers. We would like 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 II. In Section III we present a distributed algorithm to solve the problem to the optimum.

Next, in Section IV 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 [6], 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 sub-optimal solution. In Section V, we show through simulations that the values of transmit power obtained by using the proposed algorithm are close to the optimum, when it exists. If there is no optimal solution, the scheme allows us to maximize the number of simultaneous multicast transmissions that are successful.

II. 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

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transmission time and a guard time interval. Links between any pair of nodes are assumed to be bi-directional.

We focus on the case of multicast traffic connections. We assume that for each traffic connection the multicast tree has already been constructed and there is no conflict in the transmission setup, i.e., 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, i.e., sending packet traffic to the specified neighbors while meeting constraints on the SINR at the intended receivers [6].

Let us 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: $S \leq R$, i.e., 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}, i.e., $0 \leq P_k^t \leq P_{max}$. 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 are 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, i.e.,

$$\frac{a_{s(i)i} P_{s(i)}^t}{N_0 + \frac{1}{L}\sum_{k \neq s(i)} a_{ki} P_k^t} \geq \gamma_i \tag{1}$$

where a_{ki} is the propagation attenuation of the signal from transmitter k to receiver i, N_0 is the noise power, and L is the system processing gain.

Our first goal is to have the expression in (1) to be satisfied for all the nodes in $\mathcal{R}$. Thus, by defining $\vec{b} = N_0 \left[\gamma_1, \ldots \gamma_R\right]^T$ and $\vec{P^t} = \left[P_1^t, \ldots P_S^t\right]^T$, we must have

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

where $\mathbf{A}$ is an $R \times S$ matrix defined as,

$$\mathbf{A} = \begin{bmatrix} -\frac{\gamma}{L}a_{11} & \ldots & \ldots & a_{s(1)1} & \ldots - \frac{\gamma}{L}a_{S1} \\ -\frac{\gamma}{L}a_{12} & a_{s(2)2} & \ldots & \ldots & \ldots - \frac{\gamma}{L}a_{S2} \\ \vdots & \vdots & & & \vdots \\ -\frac{\gamma}{L}a_{1R} & \ldots & a_{s(R)R} & \ldots & \ldots - \frac{\gamma}{L}a_{SR} \end{bmatrix}.$$

Notice that, for each row of $\mathbf{A}$, i.e., for each receiver in $\mathcal{R}$, there is only one positive entry which corresponds to the signal received from the intended sender. All the other entries 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,

$$\mathbf{P}: \quad \text{minimize} \quad \sum_{k=1}^{S} P_k^t \tag{3}$$

$$\text{subject to} \quad \mathbf{A}\vec{P^t} \geq \vec{b} \tag{4}$$

$$0 \leq P_k^t \leq P_{max} \quad \text{for } 1 \leq k \leq S. \tag{5}$$

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 (4)–(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 (4) and (5), i.e., there is at least one set of transmission powers which ensures the successful reception at all 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 (4)–(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 Theorem 3.4 in [7]. ■

III. 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 [8], 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 sub-problems 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 sub-problems. The key of the approach presented in [8] is to use a dual formulation of the problem.

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

$$\mathbf{P'}: \quad \max_{\vec{P^t}} \quad \sum_{k=1}^{S} f(P_k^t)$$

$$\text{subject to} \quad \mathbf{A}\vec{P^t} \geq \vec{b}$$

$$0 \leq P_k^t \leq P_{max} \quad \text{for } 1 \leq k \leq S \tag{6}$$

with $f(P_k^t)$ being a twice differentiable, strictly concave function, decreasing with the increase of P_k^t. 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 to minimize the total transmit power, i.e., 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

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

where $\vec{c} = [c_1, \ldots c_R]^T$, with $c_k \geq 0$ being the cost that the kth receiver charges for all the transmitters, and $(\vec{v})_k$ denotes the kth element of the generic vector v. The term $\vec{c}^T\left(\mathbf{A}\vec{P}^t - \vec{b}\right)$ accounts for the fact that the transmission power should be sufficiently large so that the target SINR is met at each 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 [8]. Given $\vec{c}^*$, the first term in (7) is separable in P^t, so we can decompose the maximization problem into S sub-problems as follows,

$$\max_{\vec{P}^t} \sum_{k=1}^{S} f(P_k^t) + (\vec{c}^T\mathbf{A})_k P_k^t = \sum_{k=1}^{S} \max_{P_k^t}\{f(P_k^t) + (\vec{c}^T\mathbf{A})_k P_k^t\}.$$

The solution to the kth transmitter's sub-problem is given by [8]

$$P_k^t = f'^{-1}\left(-(\vec{c}^T\mathbf{A})_k\right) \quad k = 1, \ldots S \quad (9)$$

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 sub-problems.

In [8], 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 [8].

Receiver's Algorithm:

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

Transmitter's Algorithm:

1) Receive the costs from the receivers.
2) Compute the new transmit power level, P_k^t, by plugging $\vec{c}(n)$ into (9).
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 the 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 entries 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 entries 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 $\sum -P_k^t$.

Theorem 2: For the multicasting problem defined above, if the inequality $\mathbf{A}\vec{P}^t \geq \vec{\gamma}$ has a feasible solution, (i.e., there is a transmit power vector which can guarantee the SINR's at all the receivers), then there is a unique maximizer $\vec{P^t}^*$, such that:
(i) it satisfies: $\mathbf{A}\vec{P^t}^* \geq \vec{\gamma}$, and
(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 $\mathbf{A}\vec{P^t}^* \geq \vec{\gamma}$ and maximizes $\sum f(P_k^t)$ for 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 SINR's 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 with the assumption that $\vec{P^t}^*$ is a maximizer.

Now, let us consider a $S \times S$ 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 a $S \times 1$ vector $\vec{\gamma}'$ created by taking the $r(k)$'th element of $\vec{\gamma}$, for $1 \leq k \leq S$. 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 [9]. If so, we can write: $\vec{P^t}^* = (\mathbf{A}')^{-1}\vec{\gamma}'$.

By using the result proved above, we conclude that $\vec{P^t}^*$ satisfies $\mathbf{A}\vec{P^t}^* \geq \vec{\gamma}$, 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.

However, there are many situations where the power control problem $\mathbf{P}$ has no solution. In such cases, not all nodes in $\mathcal{S}$

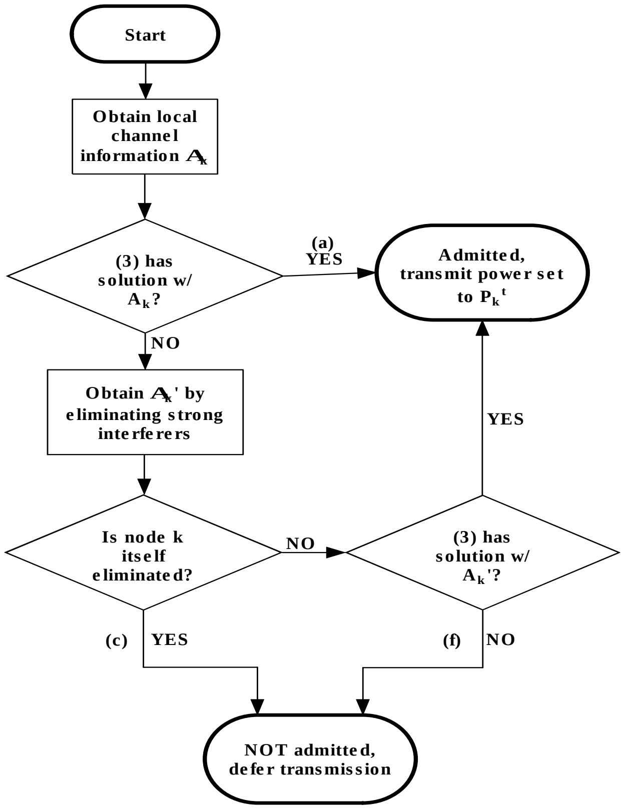


Fig. 1. Flow chart of joint scheduling and power control algorithm.

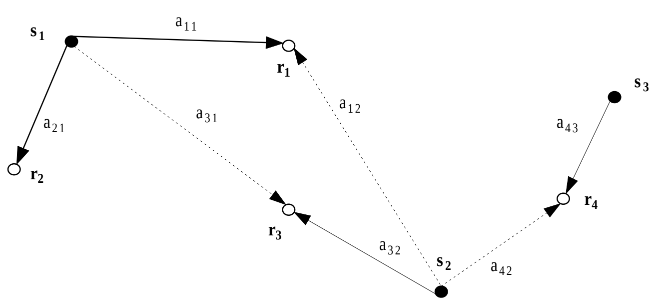


Fig. 2. An example of network with three multicast transmitters and four receivers. Each transmitter is connected to the intended receivers by solid lines and to the not intended receivers by dotted lines.

should be allowed to transmit. In the next section, we propose a scheduling algorithm, that eliminates the strongest multicast interferers and enables the nodes entitled to transmit to solve the power control problem [6].

IV. 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.

The joint scheduling and power control algorithm is described in details below, and is summarized in the flow chart shown in Fig. 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 Fig. 2, where transmitters are connected to the intended receivers by solid lines and to the not intended receivers by dotted lines. In this case, receiver r_3 estimates factors a_{31} and a_{32}, and then broadcasts such an 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 Fig. 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 Fig. 2, s_2 sends a packet including the channel attenuation factors related 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 Fig. 2, at this point s_1 knows all the channel attenuation factors but 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 (3)–(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 *Maximum Interference to Minimum Signal Ratio (MIMSR)*, which is defined as the ratio of the maximum absolute value of negative entries in row j to the minimum positive entry in row j. The MIMSR's 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 defer

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_k^t.

(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 $\mathbf{P}$ 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 sub-optimal since it is based on 'local' information only. The more negligible the entries of $\mathbf{A}$ that do not appear in the transmitters' copies of the matrix, the closer the local solution to the optimum.

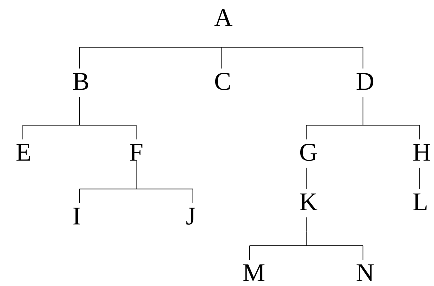
V. Simulation Results

We derive the performance of the proposed joint scheduling and power control algorithm for a stationary network whose nodes are randomly spreaded over a 100×100 square region. We focus on a multicast group composed of 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 [10]. 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 are presented in Fig. 3.

We assume that the propagation attenuation between the generic transmitter k and receiver j is $a_{kj} = 1/d_{kj}^{\alpha}$, where d_{kj} is the distance between the two nodes, and α is the power decay factor that we take to be equal to 2. The target SINR, γ, is set to 6 dB for any receiver, L is equal to 8, and P_{max} is equal to 2000.

First, we consider the case where an optimal global solution to the power control problem exists. All candidate senders are allowed to transmit and hence go through step *(a)* in the flow chart in Fig. 1. In order to derive the performance of the distributed algorithm presented in Section IV, we compute the average percentage of receivers whose SINR is less than the target threshold. We refer to these transmissions as *failed* transmissions, and plot their percentage versus the threshold β in Fig. 4. The results are independent of β, as it should be since all senders are admitted. Observe that, when the optimal solution is applied, all transmissions are successful.

The average total transmission power obtained through the proposed distributed algorithm is compared to the global optimum in Fig. 5. The sub-optimal 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 senders neglect some of the existing



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

Sender	Receiver
B	E, F
D	G, H
K	M, N

Fig. 3. A simple multicast tree with the associated transmission scheme.

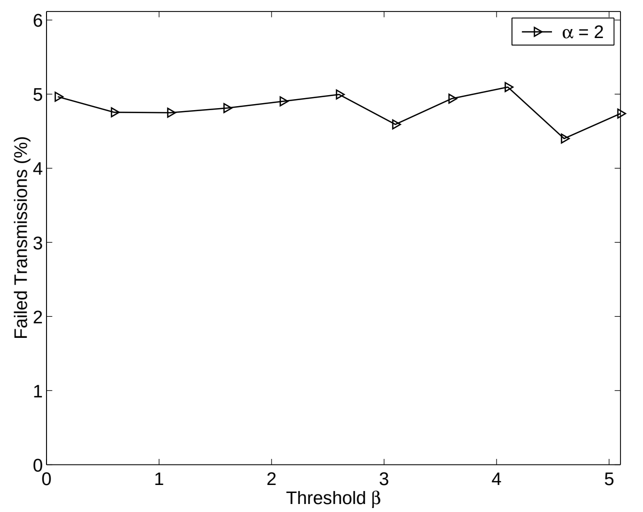


Fig. 4. Case where a global solution to the power control exists: Average percentage of receivers whose SINR is less than the target threshold as a function of β.

interferers while solving the power control problem. As a consequence, the percentage of failed transmissions that we obtain in the case of the sub-optimal solution is greater than zero (see Fig. 4), while it is equal to zero when the optimal solution is applied.

Next, we consider the case where there is no global solution to the power control problem $\mathbf{P}$. Figure 6 shows the average percentage of candidate senders that are not admitted 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 Fig. 1. On the contrary, as β becomes large, none 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 $\mathbf{P}$.

Among the admitted transmissions, we compute the average percentage of receivers whose SINR is less than the target

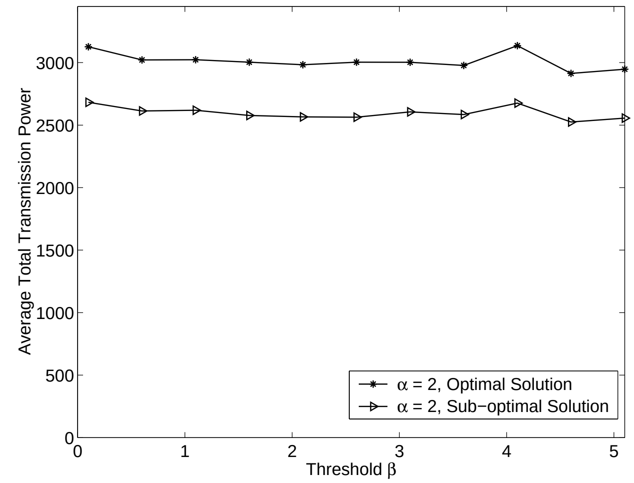


Fig. 5. Case where a global solution to the power control exists: Average total transmit power as a function of β.

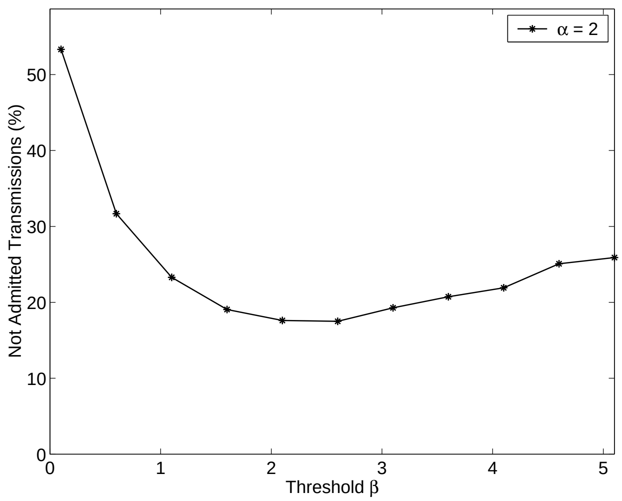


Fig. 6. Case where no global solution to the power control exists. Average percentage of candidate senders not allowed to transmit as a function of β.

threshold, i.e., the failed transmissions. The results are plotted versus β in Fig. 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 case when intermediate values of β are used. In fact, by looking at Fig. 6, we can see that less transmissions are admitted for small as well as large values of β.

The results in Figures 6–7 show 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 2 and 4.

VI. Conclusions

In this paper we addressed the problem of power control in ad hoc networks supporting multicast traffic. We first presented a distributed power control scheme, which minimizes the network power expenditure while meeting the requirements on the SINR at the receivers. However, there are sets of multicast

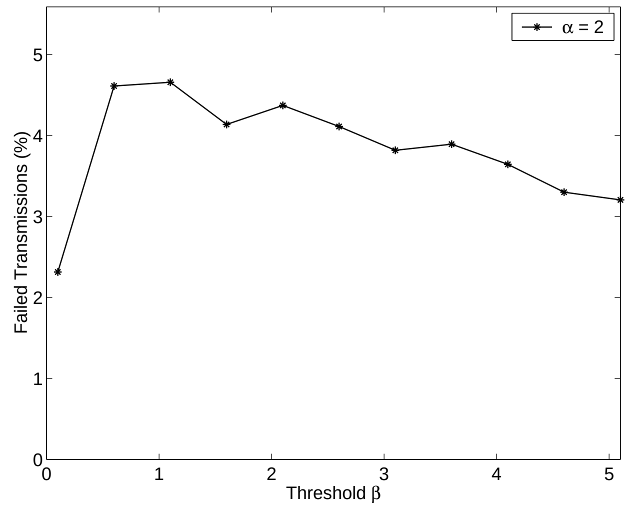


Fig. 7. Case where no global solution to the power control exists. Average percentage of receivers whose SINR is less than the target threshold as a function of β.

transmitters and receiver 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. The algorithm is based on ‘local’ information, thus providing a sub-optimal solution. Simulation results showed that the values of transmit power obtained through this algorithm are close to the optimum, when it exists. When there is not an optimal solution, the proposed scheme enables us to maximize the number of nodes that are able to successfully transmit multicast traffic.

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