A Cross-Layer Admission Control Framework for Wireless Ad-Hoc Networks using Multiple Antennas

Bechir Hamdaoui and Parameswaran Ramanathan

***Abstract*— Unlike single omnidirectional antennas, multiple antennas offer wireless ad-hoc networks potential increases in their achievable throughput and capacity. Due to recent advances in antenna technology, it is now affordable to build wireless devices with more than one antenna. As a result, multiple antennas are expected to be an essential part of next-generation wireless networks to support the rapidly emerging multimedia applications characterized by their high and diverse QoS needs. This paper develops an admission control framework that exploits the benefits of multiple antennas to better support applications with QoS requirements in wireless ad-hoc networks. The developed theory provides wireless ad-hoc networks with flow-level admission control capabilities while accounting for cross-layer effects between the PHY and the MAC layers. Based on the developed theory, we propose a mechanism that multiple antenna equipped nodes can use to control flows' admissibility into the network. Through simulation studies, we show that the proposed mechanism results in high flow acceptance rates and high network throughput utilization.**

***Index Terms*— Cross-layer admission control, quality of service (QoS), multiple antennas, wireless ad-hoc networks.**

I. Introduction

UNTIL recently, wireless ad-hoc networks were composed of nodes that are equipped with single omnidirectional antennas. Due to advances in antenna technology, it is now possible to build wireless nodes with more than one antenna. Unlike single antennas, multiple antennas, also referred to as *antenna arrays*, offer wireless ad-hoc networks potential benefits. First, they can improve the spatial reuse of the spectrum by allowing multiple simultaneous communications in the same vicinity. Second, they can increase the capacity/data rates of transmissions by exploiting the spatial division multiplexing in rich scattering environments. Third, they can increase transmission ranges by concentrating the power of transmitted signals toward desired directions. Finally, they can substantially reduce the amount of energy consumed by nodes [1] by beamforming the transmitted signals. Because of their potential benefits, multiple antennas are expected to be an essential part of next-generation wireless ad-hoc networks to face and support the rapidly emerging multimedia applications characterized by their high and diverse quality of service (QoS) requirements.

From the PHY layer's perspective, the benefits of multiple antennas are well-understood in the literature [2–6]. However, efficient exploitation of these benefits at higher layers is still under investigation [7–13]. Generally speaking, researchers have mainly focused on developing medium access control (MAC) protocols that are suited for wireless ad-hoc networks when equipped with the multiple antenna technology [8, 9, 12, 13]. The proposed MACs aim at exploiting some of the offered benefits of multiple antennas such as spatial reuse [12, 13] and spatial multiplexing [14] to provide better network utilization.

This paper develops an admission control theoretical framework that exploits the benefits of multiple antennas to better support flows with QoS needs in wireless ad-hoc networks. To the best of our knowledge, exploiting the multiple antenna benefits to provide flow-level QoS methods in wireless ad-hoc networks has not been addressed yet. The developed theory provides wireless ad-hoc networks with flow-level admission control capabilities while accounting for cross-layer effects between the PHY and the MAC layers.

The paper proceeds as follows. First, in Section II, we elaborate on the benefits of multiple antennas by providing insightful illustrations that are useful to understand the developed flow-level admission control framework. Second, in Section III, we develop a packet-level statistical framework that models the spatial reuse and the spatial multiplexing benefits offered by the array of antennas. This statistical model provides a method that each node can use to determine the amount of spatial reuse and/or multiplexing available in the node's vicinity given 1) the node's maximum transmit power, 2) the multipath nature of the wireless environment, and 3) the errors associated with the technique used by nodes to estimate the channel coefficients. Third, in Section IV, we use the proposed packet-level statistical method to develop the flow-level admission control theory. The developed theory is then used to propose a link-bandwidth calculation mechanism that wireless nodes can distributively use to determine their available bandwidths to any of their neighbors, and thus to control the admissibility of QoS flows into the network. It is important to mention that this paper does not propose a MAC protocol. In fact, the proposed admission control mechanism relies on 1) underlying MAC protocols to exchange its messages, and 2) existing routing protocols to find QoS aware routes for end-to-end flows. The effectiveness of the

Manuscript received April 14, 2006; revised July 22, 2006; accepted August 29, 2006. The associate editor coordinating the review of this paper and approving it for publication was H.-H. Chen.

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Digital Object Identifier 10.1109/TWC.2007.06040155.

mechanism is evaluated via simulations in Section V. We show that the proposed mechanism results in high end-to-end flow acceptance rates and high network throughput utilizations when used in wireless ad-hoc networks to control flows' admissibility. We also demonstrate the importance and the effect of considering cross-layer couplings into the development of admission control methods. Finally, we conclude the paper in Section VI.

II. Preliminaries

In this section, we first describe the network model and assumptions, and then provide some insightful illustrations that are useful for understanding the admission control framework developed later in the paper.

A. Model, Assumptions, and Notation

We consider a wireless ad-hoc network consisting of a finite nonempty set $\mathcal{N}$ of nodes. Each node m is equipped with an antenna array of K_m elements that it uses to transmit and receive signals. Each node is also characterized by a transmission range defined as the furthest distance that the node's transmitted signal can reach. Let $\mathcal{L} \subseteq \mathcal{N} \times \mathcal{N}$ be the set of all pairs (m, n) of distinct nodes in $\mathcal{N}$ such that m and n are within each other's transmission range. An ordered pair of nodes (m, n) in $\mathcal{L}$ is said to form a flow f if node m needs to transmit to node n. We refer to node m as the transmitter of flow f and node n as the receiver of flow f. The flow f is said to be *active* if m is currently transmitting to n; otherwise, the flow is said to be *inactive*. Let $\mathcal{F}$ denote the set of all flows. Hereafter, we model the wireless ad-hoc network as the undirected graph $G = (\mathcal{N}, \mathcal{L}, \mathcal{F})$ referred to as *node topology graph.*

Each node in the network is also assumed to be capable of estimating the coefficients of the wireless channel between it and any of its neighbors. We propose that nodes use one of the traditional techniques [1] to estimate channel coefficients and we let σ_E^2 be the estimation error variance associated with that technique. The variance σ_E^2 can be computed as $\frac{\sigma_n^2}{LE}$ where L is the length of pilot sequence per antenna, E is the transmit energy per pilot symbol per antenna, and σ_n^2 is the noise variance of channel [1]. We also assume that channel conditions remain constant over the course of any communication; i.e., nodes update their channel coefficients at the beginning of every communication and assume that these coefficients stay unchanged until the communication is finished. Sensor and mesh networks are two examples in which the channels coefficients can be safely assumed to experience little variability due to the static nature of nodes. We further assume that the wireless environment is multipath (rich scattering conditions), and hence the matrix $\mathbf{H}_{m,n}$ of channel coefficients between any pair (m, n) of nodes is of full rank. Under the multipath assumption, the elements of $\mathbf{H}_{m,n}$ can be modelled as Gaussian i.i.d random variables with zero mean and unit variance [15]. Hereafter, we use the following notation.

- $\mathbf{u}_{m,i}$: the $K_m \times 1$ *transmitting weight vector* used by node m to transmit its i^{th} stream of data on its antenna array. The j^{th} element $(u_{m,i,j})$ of $\mathbf{u}_{m,i}$ corresponds to the j^{th} element of the antenna array. If only one stream of data is being transmitted, $\mathbf{u}_m$ will then be used to denote the transmitting weight vector.
- $\mathbf{v}_{m,i}$: the $K_m \times 1$ *receiving weight vector* used by node m to receive its i^{th} stream of data on its antenna array. The j^{th} element $(v_{m,i,j})$ of $\mathbf{v}_{m,i}$ corresponds to the j^{th} element of the antenna array. If only one stream of data is being received by m, the notation $\mathbf{v}_m$ will then be used instead.
- P_m: the maximum transmit/receive power of node m normalized to the noise power. Throughout this paper, P_m will be called *maximum normalized power* of node m.
- ξ_m: the frame error rate tolerated by node m. That is, if at most $\xi_m\%$ of the packets are lost or erroneous, the quality of the communication is still considered acceptable.

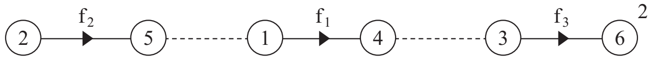


Fig. 1. Node topology graph for interference suppression illustration.

B. Interference Suppression and Signal Nulling

Consider the wireless ad-hoc network represented by the node topology graph $G = (\mathcal{N}, \mathcal{L}, \mathcal{F})$, shown in Fig. 1, where $\mathcal{N} = \{1, 2, 3, 4, 5, 6\}$, $\mathcal{L} = \{(2, 5), (5, 1), (1, 4), (4, 3), (3, 6)\}$, and $\mathcal{F} = \{f_1, f_2, f_3\}$. Now suppose that node 2 is transmitting a one-stream of data to node 5 and node 3 is also transmitting a one-stream of data to node 6 (flows f_2 and f_3 are active). Let $\mathbf{u}_2$ and $\mathbf{v}_5$ denote the transmitting and the receiving weight vectors used respectively by nodes 2 and 5 to communicate flow f_2, and $\mathbf{u}_3$ and $\mathbf{v}_6$ denote those used by nodes 3 and 6 to communicate flow f_3. Here, we want to find out whether node 1 can transmit to node 3 in concurrence with node 3's transmission and node 5's reception and, if so, how this is possible.

In order for f_1, f_2, and f_3 to be active concurrently, one needs to ensure the following: 1) node 1's signal must achieve a unit gain at node 4; 2) node 2's signal must achieve a unit gain at node 5; 3) node 3's signal must achieve a unit gain at node 6; 4) node 1's signal must be nulled (or suppressed) at node 5; and 5) node 3's signal must be nulled (or suppressed) at node 4. In terms of equations, one can write

$$\begin{cases} \mathbf{u}_1^T \mathbf{H}_{1,4} \mathbf{v}_4 = 1, & \text{1's signal received at 4;} \quad \text{(a)} \\ \mathbf{u}_2^T \mathbf{H}_{2,5} \mathbf{v}_5 = 1, & \text{2's signal received at 5;} \quad \text{(b)} \\ \mathbf{u}_3^T \mathbf{H}_{3,6} \mathbf{v}_6 = 1, & \text{3's signal received at 6;} \quad \text{(c)} \\ \mathbf{u}_1^T \mathbf{H}_{1,5} \mathbf{v}_5 = 0, & \text{1's signal suppressed at 5;} \quad \text{(d)} \\ \mathbf{u}_3^T \mathbf{H}_{3,4} \mathbf{v}_4 = 0, & \text{3's signal suppressed at 4.} \quad \text{(e)} \end{cases} \quad (1)$$

There are two approaches that one can use to design weight vectors $\mathbf{u}_1$, $\mathbf{u}_2$, $\mathbf{u}_3$, $\mathbf{v}_4$, $\mathbf{v}_5$, and $\mathbf{v}_6$ so that flows f_1, f_2, and f_3 can be active simultaneously (e.g., satisfy all the equations of System (1)).

1) Centralized Approach: One approach is to formulate the problem as the following global minimization problem. Find the weight vectors $\mathbf{u}_1$, $\mathbf{u}_2$, $\mathbf{u}_3$, $\mathbf{v}_4$, $\mathbf{v}_5$, and $\mathbf{v}_6$ that minimize the total power[1], $\sum_{m=1}^{3}||\mathbf{u}_m||^2 + \sum_{n=4}^{5}||\mathbf{v}_n||^2$, subject to: Eqs. (1)(a)-(e); $||\mathbf{u}_m||^2 \leq P_m$ for $m = 1,2,3$; and $||\mathbf{v}_n||^2 \leq P_n$ for $n = 4,5,6$. Although, the global minimization formulation provides solutions, if any exist, that would always provide optimal spatial multiplexing/reuse, it is not practically attractive for three reasons. First, it requires the knowledge of global information and hence a global center to gather the information and solve the problem. Second, it may require the readjustment of weight vectors of nodes already involved in ongoing transmissions and/or receptions. For example, the global solution may be such that the new transmitting weight vector $\mathbf{u}_3$ is different from that used before the new flow f_1 emerged. This causes an extra control overhead since node 3 will have to readjust its weight vector $\mathbf{u}_3$ to the new solution obtained from solving the global optimization problem. Third, the problem is not linear. Hence it cannot be solved by traditional linear programming methods; i.e., it requires more complex techniques. This approach could, however, serve as a baseline on how much spatial reuse and/or spatial multiplexing a node can obtain.

2) Distributed Approach: A second approach is to decentralize the global optimization problem described above into two local optimization problems. In this approach, we let the transmitter of the new emerging flow be responsible for nulling its signal at all nearby receivers. Also, we let the receiver of the new emerging flow be responsible for suppressing the interference caused by all nearby transmitters. This approach requires that the new transmitter cooperate with all of its nearby interfering receivers (i.e., by exchanging weight vectors among each others) to determine its optimal transmitting weight vector. Similarly, it requires that the new receiver cooperate with all of its nearby transmitters to determine its optimal receiving weight vector. The new transmitter needs then to solve a local minimization problem which consists of minimizing its total power subject to making sure that its signal is nulled at all nearby receivers while achieving a unit gain at the desired receiver. Likewise, the new receiver is required to solve a local minimization problem consisting of minimizing its total power subject to suppressing the interference coming from all nearby transmitters. Let's consider the example again for illustration. The transmitter of the new flow (node 1) can cooperate with its nearby receiver (node 5) to locally solve for $\mathbf{u}_1$. Here, for example, node 5 sends its receiving weight vector $\mathbf{v}_5$ to node 1 which uses to solve its local minimization problem; i.e., find $\mathbf{u}_1$ that minimizes $||\mathbf{u}_1||^2$ subject to Eqs. (1)(a) and (d).

Unlike the global minimization approach, this approach is distributive in that it requires a cooperative exchange of information among neighbor nodes only to design weight vectors satisfying all the equations of System (1). In addition, the constraints of this approach are linear and hence the two local minimization problems require simple methods to solve (in fact, as we see later, each problem has a closed-form solution). Another advantage of this approach is that it does not require the readjustment of weight vectors of nodes already involved in ongoing communications (e.g., readjustment of $\mathbf{u}_3$ or $\mathbf{v}_5$). Due to its simplicity and practicality, in this work, we consider this distributed approach to exploit the spatial reuse and the spatial multiplexing benefits offered by the adaptive antenna arrays.

[1]It is not necessary to optimize w.r.t power consumption to illustrate the point we are trying to make here; in fact, all what one needs is a feasible solution. The reason for choosing power consumption as an objective will, however, become clear later in Sections II-C and II-D.

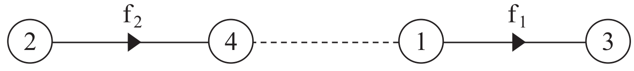


Fig. 2. Node topology graph for power illustration.

C. Spatial Reuse Versus Spatial Division Multiplexing

Consider the wireless ad-hoc network $G = (\mathcal{N}, \mathcal{L}, \mathcal{F})$, as shown in Fig. 2, where $\mathcal{N} = \{1,2,3,4\}$, $\mathcal{L} = \{(1,3),(2,4),(1,4)\}$, and $\mathcal{F} = \{f_1, f_2\}$. Assume that the number of antennas are such that $K_1 = K_3 = 1$ and $K_2 = K_4 = 2$. Also, assume that f_1 and f_2 are the only two flows in the network; i.e., node 1 has data to send to node 3 and node 2 has data to send to node 4.

Let's suppose that while node 1 is transmitting to node 3 (i.e., flow f_1 is active), node 2 wants to transmit to node 4. Let $\mathbf{u}_1$ be the (1×1) transmitting weight vector that node 1 is currently using to weigh its transmitted signal and $\mathbf{v}_3$ be the (1×1) receiving weight vector that node 3 is currently using to weigh the signal received from node 1. In order for node 4 to receive an interference-free signal from node 2, it must design its receiving weight vector $\mathbf{v}_4$ in such a way that it suppresses the interference caused by node 1's transmission while assuring an acceptable gain (e.g., unit) of its intended signal coming from node 2. In terms of equations, these constraints can be written as $(\mathbf{u}_2^T\mathbf{H}_{2,4})\mathbf{v}_4 = 1$ and $(\mathbf{u}_1^T\mathbf{H}_{1,4})\mathbf{v}_4 = 0$ where $\mathbf{u}_2 = [u_{2,1}\ u_{2,2}]^T$ is the transmitting weight vector of node 2 and $\mathbf{v}_4 = [v_{4,1}\ v_{4,2}]^T$ is the receiving weight vector of node 4. Because the elements of each of $\mathbf{H}_{1,4}$ and $\mathbf{H}_{2,4}$ are i.i.d, there exists a unique solution $\mathbf{v}_4^*$ to the system of these two equations; i.e., knowing $\mathbf{H}_{1,4}$, $\mathbf{H}_{2,4}$, $\mathbf{u}_1$, and $\mathbf{u}_2$, node 4 can solve the system of the two equations to determine $\mathbf{v}_4^*$. Hence if there is no limit on node 4's receive power, it is always possible for node 4 to receive one interference-free stream of data from node 2 concurrently with node 1's transmitted signal. Hence, multiple antennas may increase the spatial reuse by allowing concurrent flows in the same vicinity; i.e., because of node 4's two antennas, f_1 and f_2 can both be active simultaneously.

Now suppose that node 1 is not currently transmitting. Node 4 can then use both of its degrees of freedom (i.e., both antennas) to receive two streams of data concurrently. To design its receiving weight vectors $\mathbf{v}_{4,1} = [v_{4,1,1}\ \ v_{4,1,2}]^T$ and $\mathbf{v}_{4,2} = [v_{4,2,1}\ \ v_{4,2,2}]^T$, node 4 will then have to solve the following two systems each of two linear equations: $(\mathbf{u}_{2,1}^T\mathbf{H}_{2,4})\mathbf{v}_{4,1} = 1$, $(\mathbf{u}_{2,2}^T\mathbf{H}_{2,4})\mathbf{v}_{4,1} = 0$ and $(\mathbf{u}_{2,1}^T\mathbf{H}_{2,4})\mathbf{v}_{4,2} = 0$, $(\mathbf{u}_{2,2}^T\mathbf{H}_{2,4})\mathbf{v}_{4,2} = 1$. The vectors $\mathbf{u}_{4,1} = [u_{4,1,1}\ \ u_{4,1,2}]^T$ and $\mathbf{u}_{4,2} = [u_{4,2,1}\ \ u_{4,2,2}]^T$ are the two transmitting weight vectors used by node 2 to transmit its two streams. Again under the rich scattering environment assumption, each of the above two systems has a unique solution, $\mathbf{v}_{4,1}^*$ and $\mathbf{v}_{4,2}^*$. Without power limitation, node 4 can always receive two concurrent data streams by weighing its received signal using the two solutions $\mathbf{v}^*_{4,1}$ and $\mathbf{v}^*_{4,2}$. Note that now node 1 cannot transmit without causing interference at node 4 (spatial reuse is not possible now). This is because both of node 4's degrees of freedom are used to receive the two-stream flow via exploitation of the spatial division multiplexing offered by its antenna array.

To summarize, a node's degrees of freedom (number of antennas) can be exploited in one of three ways: 1) all degrees are used to send a multiple-stream flow of data by exploiting the spatial division multiplexing of the antenna array; 2) all degrees of freedom are used to increase the spatial reuse of the spectrum by allowing multiple concurrent streams in the same vicinity; 3) some of the degrees are used to send a multiple-steam flow while the others are used to allow for concurrent streams in the same neighborhood.

D. Physical Limitations

Note that the level of exploitation of the spatial reuse and/or multiplexing offered by the antenna arrays is contingent on physical limitations such as node's power, multipath, and/or channel estimation errors. For instance, referring to the example in Section II-C for illustration, note that it is the existence of the solution $\mathbf{v}^*_4$ that allows node 4 to receive its interference-free signal concurrently with node 1's transmission. However, if $\mathbf{v}^*_4$ is such that $||\mathbf{v}^*_4||^2 > P_4$, then node 4 can no longer receive an interference-free signal.

Hence, when a node is equipped with K-element antenna array (K degrees of freedom), it does not mean that K concurrent streams (spatial reuse and/or multiplexing) can occur within the node's vicinity; physical constraints may restrict the number of the possible concurrent streams to be less than K. In the next section, we develop a theoretical framework that captures the spatial reuse and/or multiplexing benefits of multiple antennas while accounting for physical limitations.

III. Packet-level Analysis

Consider two neighbor nodes m and n respectively with K_m and K_n antennas. Suppose that m wants to transmit an α-stream flow f of data to n. Let's also suppose that there are β streams currently received by nodes located within m's transmission range, and γ streams currently transmitted by nodes located within n's reception range. As mentioned in Section II-D, although node m is left with $K_m - \beta$ degrees of freedom that it can exploit to send a multiple-stream signal with up to $K_m - \beta$ streams, it may actually be able to transmit only $\alpha < K_m - \beta$ streams due to power limitation. In other words, the number $(\alpha + \beta)$ of concurrent streams in the vicinity of m is likely to be less than its number of degrees of freedom K_m. Due to similar reasons, node n may not be able to successfully receive $\alpha = K_n - \gamma$ streams even though n is left with $K_n - \gamma$ degrees of freedom. Hence, the number $(\alpha + \gamma)$ of concurrent streams in the vicinity of n is likely to be less than its number of degrees of freedom K_n. The objective of this section is to statistically derive the two numbers $M_t(f) \equiv (\alpha + \beta) \leq K_m$ and $M_r(f) \equiv (\alpha + \gamma) \leq K_n$ given the statistical characteristics of the wireless channel and the availability/limitation of network resources. The numbers $M_t(f)$ and $M_r(f)$, which respectively capture the transmission capabilities of m and reception capabilities of n, will be used to provide flow-level admission control methods as we shall see in Section IV.

To derive $M_t(f)$ and $M_r(f)$, we proceed as follows. First, provided that there are β streams currently received by nodes located within m's transmission range, we derive the probability $\mathcal{P}_t(\alpha, \beta)$ of m successfully transmitting an α-stream signal to n without causing interference to any of the β nearby streams. Likewise, we derive the probability $\mathcal{P}_r(\alpha, \gamma)$ of n receiving an interference-free α-stream signal from m provided that there are γ streams currently transmitted by nodes located within its reception range. Both probabilities are derived based on 1) the statistics of the wireless channel, 2) the channel estimation errors, 3) the nodes' power availability, and 4) the network topology. Second, given that at most $\xi_m\%$ of m's packets can be erroneous while having an acceptable quality of communication, we use the derived probability $\mathcal{P}_t(\alpha, \beta)$ to determine $M_t(f)$. Similarly, given ξ_n, we use $\mathcal{P}_r(\alpha, \gamma)$ to determine $M_r(f)$.

A. Derivation of $\mathcal{P}_t(\alpha, \beta)$ and $\mathcal{P}_r(\alpha, \gamma)$

Let $\{m_1, m_2, \ldots, m_p\}$ denote the set of m's neighbors that are receiving the β streams and β_i denote the number of streams that node m_i is currently receiving for all $i \in \{1, 2, \ldots, p\}$ (i.e., $\sum_{i=1}^{p} \beta_i = \beta$). Similarly, let $\{n_1, n_2, \ldots, n_q\}$ denote the set of n's neighbors that are transmitting the γ streams and γ_i denote the number of streams out of γ that node n_i is transmitting for all $i \in \{1, 2, \ldots, q\}$ (i.e., $\sum_{i=1}^{q} \gamma_i = \gamma$). For each $i = 1, 2, \ldots p$, we assume that m knows the receiving weight vector of m_i as well as the channel matrix between it and m_i. Similarly, we assume that n knows the transmitting weight vector of each n_i and the channel matrix between it and n_i for all $i = 1, 2, \ldots, q$.

1) Error-Free Channel Coefficient Estimation: Node m can design its α transmitting weight vectors $\mathbf{u}^*_{m,j}$, $j = 1, 2, \ldots, \alpha$, by solving the following optimization problem

$$\Pi_t : \quad \begin{array}{ll} \text{minimize} & \sum_{j=1}^{\alpha} ||\mathbf{u}_{m,j}||^2 \\ \text{subject to} & \mathbf{A}_m \mathbf{u}_{m,j} = \mathbf{a}_j, \quad j = 1, 2, \ldots, \alpha \end{array}$$

where $\mathbf{a}_j$ is the column vector of length $\alpha + \beta$ defined as $[0\,0 \ldots 0\,1\,0\,0 \ldots 0]^T$ (1 is at the j^{th} position), and $\mathbf{A}_m$ is the $\alpha+\beta$ by K_m matrix defined as $[\tilde{\mathbf{A}}_{m,n}\ \tilde{\mathbf{A}}_{m,1}\ \tilde{\mathbf{A}}_{m,2} \ldots \tilde{\mathbf{A}}_{m,p}]^T$ with $\tilde{\mathbf{A}}_{m,n} = [\mathbf{H}_{m,n}\mathbf{v}_{n,1}\ \ \mathbf{H}_{m,n}\mathbf{v}_{n,2} \ldots \mathbf{H}_{m,n}\mathbf{v}_{n,\alpha}]$ and $\tilde{\mathbf{A}}_{m,i} = [\mathbf{H}_{m,m_i}\mathbf{v}_{m_i,1}\ \mathbf{H}_{m,m_i}\mathbf{v}_{m_i,2} \ldots \mathbf{H}_{m,m_i}\mathbf{v}_{m_i,\beta_i}]$ for all $i = 1, 2, \ldots, p$. Similarly, node n can design its receiving weight vectors $\mathbf{v}^*_{n,j}$, $j = 1, 2, \ldots, \alpha$, by solving the following optimization problem

$$\Pi_r : \quad \begin{array}{ll} \text{minimize} & \sum_{j=1}^{\alpha} ||\mathbf{v}_{n,j}||^2 \\ \text{subject to} & \mathbf{B}_n \mathbf{v}_{n,j} = \mathbf{b}_j, \quad j = 1, 2, \ldots, \alpha \end{array}$$

where $\mathbf{b}_j$ is the column vector of length $\alpha + \gamma$ defined as $[0\,0 \ldots 0\,1\,0\,0 \ldots 0]^T$ (1 is at the j^{th} position), and $\mathbf{B}_n$ is the $\alpha + \gamma$ by K_n matrix defined as $[\tilde{\mathbf{B}}_{m,n}\ \tilde{\mathbf{B}}_{1,n}\ \tilde{\mathbf{B}}_{2,n} \ldots \tilde{\mathbf{B}}_{q,n}]^T$ with $\tilde{\mathbf{B}}_{m,n} = [\mathbf{H}^T_{m,n}\mathbf{u}_{m,1}\ \ \mathbf{H}^T_{m,n}\mathbf{u}_{m,2} \ldots \mathbf{H}^T_{m,n}\mathbf{u}_{m,\alpha}]$ and $\tilde{\mathbf{B}}_{i,n} = [\mathbf{H}^T_{n_i,n}\mathbf{u}_{n_i,1}\ \mathbf{H}^T_{n_i,n}\mathbf{u}_{n_i,2} \ldots \mathbf{H}_{n_i,n}\mathbf{u}_{n_i,\gamma_i}]$ for all $i = 1, 2, \ldots, q$.

Clearly, if $\alpha + \beta > K_m$ or $\alpha + \gamma > K_n$, node m cannot transmit any stream to n without interfering with at least one of the other streams. Hereafter, we assume that $\alpha + \beta \leq K_m$ and $\alpha + \gamma \leq K_n$.

Theorem 1: Π_t and Π_r each has a unique solution given respectively by $\mathbf{u}^*_{m,j} = \mathbf{A}^T_m(\mathbf{A}_m\mathbf{A}^T_m)^{-1}\mathbf{a}_j$ and $\mathbf{v}^*_{n,j} = \mathbf{B}^T_n(\mathbf{B}_n\mathbf{B}^T_n)^{-1}\mathbf{b}_j$, for $j = 1, 2, \ldots, \alpha$.

PROOF: The proof is not included due to space limitation.■

The optimal values P^*_m (the minimum possible transmit power of m normalized to the noise power) and P^*_n (the minimum possible receive power of n normalized to the noise power) of respectively Π_t and Π_r are then given by $P^*_m = \sum_{j=1}^{\alpha} \mathbf{a}^T_j(\mathbf{A}_m\mathbf{A}^T_m)^{-1}\mathbf{a}_j$ and $P^*_n = \sum_{j=1}^{\alpha} \mathbf{b}^T_j(\mathbf{B}_n\mathbf{B}^T_n)^{-1}\mathbf{b}_j$. After determining their optimal weight vectors by solving Π_t and Π_r, nodes m and n need then to verify that their power budgets are not violated. That is, node m can transmit each of its α streams to node n without causing interference only if $P^*_m \leq P_m$ and $P^*_n \leq P_n$.

It is important to note that both solutions $\mathbf{u}^*_{m,j}$ and $\mathbf{v}^*_{n,j}$ are instantaneous in the sense that they must be determined on a packet-by-packet basis. If any of the nodes in $\{m_1, m_2, \ldots, m_p\}$ or $\{n_1, n_2, \ldots, n_q\}$ decide not to be receiving or other nearby nodes happen to be receiving during the transmission of the next packet, then any of $\mathbf{u}^*_{m,j}$ and $\mathbf{v}^*_{n,j}$ may not be solutions anymore and hence any of $P^*_m \leq P_m$ and $P^*_n \leq P_n$ may no longer hold. In other words, while it may currently be possible to transmit while having a certain number of interferers in the same vicinity, it may not be possible during the course of the next packet transmission if the number of interferers changes. Moreover, even if the number of interferers remain unchanged during the next packet transmission, being able to transmit the current packet does not mean that it would be possible to transmit the next one. This is due to the fact that channel coefficients are variant both over time and from one node to another. At the packet granularity, this does cause any problem since nodes will have to solve Π_t or Π_r on a packet-by-packet basis to determine whether it would be possible for them to carry interference-free communications. At the flow-level, however, one needs to be able to provide guarantees on meeting all long-term rates of the currently admitted flows. Flow-level rate guarantees will be the focus of the next section. Here we provide packet-level statistical guarantees by deriving the probabilities of successfully carrying α communications in concurrence with β receptions within the sender's transmission range and γ transmissions within the receiver's reception range. These probabilities will be useful for the flow-level analysis as we shall see in Section IV.

Let's assume that all the α streams consume the same amount of power. Hence m and n can at most utilize $\frac{P_m}{\alpha}$ and $\frac{P_n}{\alpha}$ to respectively transmit and receive each of the α streams. For every stream $j = 1, 2, \ldots, \alpha$, the optimal amount of transmit power consumed by j is $P^*_{m,j} = \mathbf{a}^T_j(\mathbf{A}_m\mathbf{A}^T_m)^{-1}\mathbf{a}_j$. Likewise, the optimal amount of power that node n uses to receive j is $P^*_{n,j} = \mathbf{b}^T_j(\mathbf{B}_n\mathbf{B}^T_n)^{-1}\mathbf{b}_j$. Since the elements of $\mathbf{A}_m$ and $\mathbf{B}_n$ can each be modelled as Gaussian i.i.d random variable with zero mean and unit variance [16], $\mathbf{A}_m$ and $\mathbf{B}_n$ are of rank $\alpha + \beta$ and $\alpha + \gamma$ respectively. Thus the random variables X_t and X_r defined as $X_t \equiv \frac{1}{P^*_{m,j}} = \frac{\mathbf{a}^T_j\mathbf{a}_j}{\mathbf{a}^T_j(\mathbf{A}_m\mathbf{A}^T_m)^{-1}\mathbf{a}_j}$ and $X_r \equiv \frac{1}{P^*_{n,j}} = \frac{\mathbf{b}^T_j\mathbf{b}_j}{\mathbf{b}^T_j(\mathbf{B}_n\mathbf{B}^T_n)^{-1}\mathbf{b}_j}$ for any $j = 1, 2, \ldots, \alpha$, are known to both have a chi-squared distribution respectively with $K_m - \alpha - \beta + 1$ and $K_n - \alpha - \gamma + 1$ degrees of freedom [17]. Taking into account the power constraints and following similar analysis to [16], the probabilities $\mathcal{P}_t(\alpha, \beta)$ and $\mathcal{P}_r(\alpha, \gamma)$ can be written as

TABLE I
$\mathcal{P}_t(\alpha, \beta)$ FOR $K_m = 3$.

	$\beta = 2$	$\beta = 1$		$\beta = 0$		
	$\alpha = 1$	$\alpha = 1$	$\alpha = 2$	$\alpha = 1$	$\alpha = 2$	$\alpha = 3$
$P_m = 0$ dB	31.7	60.6	15.7	80.1	36.7	8.3
$P_m = 14$ dB	65.5	90.4	52.7	97.8	81.8	43.8
$P_m = 20$ dB	75.2	95.1	65.5	99.2	90.5	58.4

$$\mathcal{P}_t(\alpha, \beta) = \int_{\frac{\alpha}{P_m}}^{\infty} c_{K_m-\alpha-\beta+1}(x)dx \tag{2}$$

and

$$\mathcal{P}_r(\alpha, \gamma) = \int_{\frac{\alpha}{P_n}}^{\infty} c_{K_n-\alpha-\gamma+1}(x)dx \tag{3}$$

where $c_i(x)$ is the central chi-squared distribution with i degrees of freedom for $i = K_m - \alpha - \beta + 1, K_n - \alpha - \gamma + 1$. In Table I, we provide a numerical example showing $\mathcal{P}_t(\alpha, \beta)$ for different combinations of α, β, and P_m when $K_m = 3$. For example, suppose that the maximum transmit power of m (normalized to the noise power) is $P_m = 20$ dB and there is one stream currently received by a node located within m's transmission range ($\beta = 1$). Node m then has a 95.1% chance of successfully transmitting a stream of data to n ($\alpha = 1$) without causing interference to its nearby received stream.

There are two points that require attention regarding the error-free channel estimation based probabilities $\mathcal{P}_t(\alpha, \beta)$ and $\mathcal{P}_r(\alpha, \gamma)$, given respectively by Eqs. (2) and (3). First, for a fixed sum $(\alpha + \beta)$, it can easily be seen from Eq. (2) that larger values of α—and hence smaller values of β—result in lower chances of having $\alpha + \beta$ successful and concurrent communications in the sender's vicinity. However, decreasing α in detriment of increasing β to keep the sum $(\alpha + \beta)$ constant will result in higher chance of concurrent success of the $\alpha + \beta$ communications. Referring to the example illustrated in Table I, when $P_m = 20$ dB, the chances of success when $(\alpha = 1, \beta = 2)$ are 75.2%; whereas those when $(\alpha = 2, \beta = 1)$ are 65.5%. Hence, although $\alpha + \beta$ is kept equal to 3, higher α results in lower chances. Similar analysis applies to the reception case. For a fixed sum $(\alpha+\gamma)$, it follows from Eq. (3) that larger values of α result in lower chances of having $\alpha + \gamma$ successful communications in the receiver's vicinity. Therefore, one can conclude that exploiting spatial reuse is more desirable than exploiting spatial multiplexing since the former results in higher chances of success. The second point that is also important to mention is that due to perfect channel coefficient estimation, the ability of receiving one or more interference-free streams depends only on the number of nearby current transmitters and not on their power levels. As we shall see in the next section, this is no longer true when we consider an imperfect channel estimation method.

2) Erroneous Channel Coefficient Estimation: Due to the imperfectness of the channel estimation method, real channel coefficients are likely to differ from those estimated ones. Therefore, the α streams may cause unexpected interference to any of the β nearby streams due to m's imperfect nulling. Likewise, any of the α streams received at n may experience unexpected interference due to n's imperfect interference suppression of signal coming from the γ nearby streams. This undesired interference typically degrades the signal to interference and noise ratios (SINRs) of the affected receivers including node n. One way of improving the SINR at node n is to increase the power $P^*_{m,j}$ at which stream j is transmitted. This, however, in turn will increase the amount of interference any of the β streams may experience resulting in further decrease in their SINRs. Instead, we propose that the sender (e.g., node m) must have enough transmit power to combat the worst case interference that its desired receiver (e.g., node n) might experience before transmitting.

The excess interference power experienced at node n due to n's neighbor k's transmission of a given stream j is $\sigma_E^2 P^*_{k,j}$ where again σ_E^2 is the channel estimation error and $P^*_{k,j}$ is the optimal power level used by node k to transmit its j^{th} stream. Now let's see how much excess interference any given m's stream j_0, $1 \le j_0 \le \alpha$, received at n would experience due to all n's nearby transmitted streams, including the other $\alpha - 1$ streams transmitted by m and interfere with j_0. If we let ΔP^*_n denote such excess interference, then one can write

$$\begin{aligned}\Delta P^*_n &= \left\{\sum_{j=1,j\neq j_0}^{\alpha} P^*_{m,j} + \sum_{i=1}^{q}\sum_{j=1}^{\gamma_i} P^*_{n_i,j}\right\}\sigma_E^2\\ &= \left\{\frac{\alpha-1}{\alpha}P^*_m + \sum_{i=1}^{q} P^*_{n_i}\right\}\sigma_E^2.\end{aligned}$$

If we consider the worst-case scenario where all n's nearby streams are transmitted at their maximum power levels and if we let P_{max} denote the highest power level that any node could transmit at, then the amount of the worst-case interference ΔP_n experienced by node n's j^{th} stream can be written as $\Delta P_n = (\frac{\alpha-1}{\alpha} + q)P_{max}\sigma_E^2$. Now when considering the above interference ΔP_n, the probability $\mathcal{P}_t(\alpha,\beta)$ of having node n receive successfully any one of the α streams in concurrence with q nearby transmitters can be written as $\mathcal{P}_t(\alpha,\beta) = \int_{\frac{\alpha(1+\Delta P_n)}{P_m}}^{\infty} c_{K_m-\alpha-\beta+1}(x)dx$.

Recall that our approach proposes that in order for a transmitter m to communicate with a receiver n, m must be able to null its signal at all its nearby receivers and n must be able to suppress the interference caused by all its nearby transmitters. As just discussed above, due to imperfect interference suppression, the transmitter m must also account for the unexpected interference caused by the q current transmitters located in the vicinity of n when deciding whether it will be able to successfully transmit to n.

Suppose that based on m's current state (power availability, the number of n's nearby transmitters, and channel information), m finds out that it is capable of nulling its signal at all its nearby receivers as well as combating the unexpected interference experienced by n and hence it can successfully communicate with n. Now suppose that just after m started transmitting to n, one or more nodes that happen to be n's neighbors decide to transmit (they were not active transmitters when m was deciding to transmit). Although, these nodes must have already nulled their signals at all nearby receivers including n, they may still cause undesired interference at n due to errors in their estimated channel coefficients. This may cause an unexpected SINR degradation at n which, in turn, may result in an unsuccessful communication between m and n. There are two ways of dealing with this problem. One way is to ignore it; i.e., let packets be retransmitted whenever n is not able to decode them due to excessive interference. Another way is to consider the more conservative interference case. Instead of considering the interference caused by only the q nearby and current transmitters, we consider the interference that would have been caused if all the neighbors of n transmit at their peak powers. Hence, if we let $\kappa(n)$ denote the number of all neighbors of n and $\Delta P'_n = (\frac{\alpha-1}{\alpha} + \kappa(n))P_{max}\sigma_E^2$, the probability $\mathcal{P}_t(\alpha,\beta)$ of having node n receive successfully any one of the α streams can now be written as

$$\mathcal{P}_t(\alpha,\beta) = \int_{\frac{\alpha(1+\Delta P'_n)}{P_m}}^{\infty} c_{K_m-\alpha-\beta+1}(x)dx. \quad (4)$$

Recall that, in the erroneous channel estimation case, receivers still compute their $\mathcal{P}_r(\alpha,\beta)$ as in the error-free channel estimation case, given by Eq. (3).

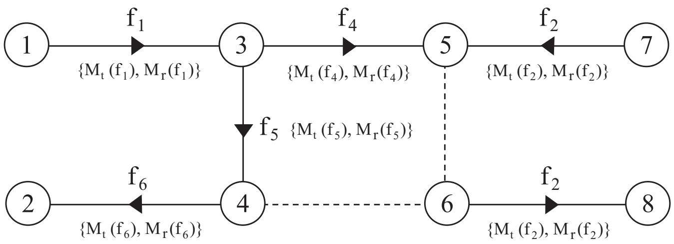
B. Transmit/Receive Degrees of Freedom: $M_t(f)$ and $M_r(f)$

Again, suppose that a node m wants to transmit an α-stream flow f of data to a neighbor node n. Given α and ξ_n, one can use Eq. (3) to determine the number γ, and hence, the number $(\alpha+\gamma)$, such that $\mathcal{P}_r(\alpha,\gamma) \ge 1-\xi_n$. We call the number $(\alpha+\gamma)$, corresponding to the largest α such that $\mathcal{P}_r(\alpha,\gamma) \ge 1-\xi_n$, *receive degrees of freedom* of f and denote it by $M_r(f)$. Recall from Section III-A.1 that for a fixed sum $(\alpha+\gamma)$, larger values of α result in lower chances of having $\alpha+\gamma$ successful communications in n's vicinity; i.e, given ξ_n, the larger α, the smaller $(\alpha+\gamma)$. Note that because $M_r(f)$ is to be used in next section to develop flow-level admission conditions, we chose it to be the one that corresponds to the worst-case scenario; i.e., when α is the largest. As for m's transmission capability, the probability $\mathcal{P}_t(\alpha,\beta)$ depends not only on the sum $(\alpha+\beta)$ and the number α, but also on the number of n's nearby neighbors $\kappa(n)$. Similarly, given α, ξ_m and $\kappa(n)$, m can use Eq. (4) to compute the number $M_t(f) \equiv (\alpha+\beta) \le K_m$ that corresponds to the largest α such that $\mathcal{P}_t(\alpha,\beta) \ge 1-\xi_m$. We will refer to $M_t(f)$ as *transmit degrees of freedom* of f.

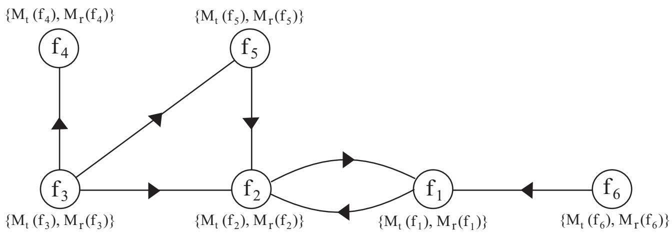
Note that both the transmit and the receive degrees of freedom may differ from one flow to another due to the fact that nodes may have different acceptable frame error rates, different maximum transmit/receive power, and/or different number of neighbors. Hence, hereafter, each flow f will be characterized by two numbers $M_t(f)$ and $M_r(f)$. These two statistical numbers will be used to provide data rate guarantees at the flow level, as we shall show in Section IV.

IV. Flow-level Admission Control

In the previous section, we described the transmission and the reception capabilities of nodes from a packet-level's standpoint. Based on channel estimation errors, channel statistics, and power availability, we derived a probabilistic transmit



(a) Node topology graph $G = (\mathcal{N}, \mathcal{L}, \mathcal{F})$.



(b) Flow interference graph $H = (\mathcal{F}, \mathcal{E})$.

Fig. 3. Illustrative network graphs.

and receive degrees of freedom that both capture the tradeoff between the spatial multiplexing and the spatial reuse benefits offered by the multiple antennas. Although packet-level analysis alone cannot provide guarantees that can be used to control flow admissibility, it is an essential step toward developing flow-level admission control conditions. In this section, we use the packet-level analysis to derive flow-level sufficient conditions under which the rates of all current admitted flows in the network are guaranteed (statistically) to be met.

A. Node Topology and Flow Interference Graphs

Let's associate each flow f in $\mathcal{F}$ with the pair $(M_t(f), M_r(f))$ of the transmit and the receive degrees of freedom as determined in Section III-B. We represent the wireless network via two graphs: *node topology graph* and *flow interference graph*. The former graph is an extension of the node topology graph $G = (\mathcal{N}, \mathcal{L}, \mathcal{F})$ defined in Section II-A to include all pairs $(M_t(f), M_r(f))$ associated with all flows $f \in \mathcal{F}$. Recall that each link $l \in \mathcal{L}$ corresponds to an unordered pair of neighbor nodes in $\mathcal{N}$ whereas each flow $f \in \mathcal{F}$ is formed by an ordered pair of nodes $(m, n) \in \mathcal{L}$ such that m has data to transmit to n. We refer to m as the transmitter of flow f and n as the receiver of flow f. We show an illustrative example of a node topology graph in Fig. 3(a) where circles represent element of $\mathcal{N}$; lines (both dashed and continuous) represent elements of $\mathcal{L}$; and arrows represent elements of $\mathcal{F}$. For every node $m \in \mathcal{N}$, we let $\mathcal{F}_t(m)$ denote the set of all flows whose transmitter node is m, and $\mathcal{F}_r(m)$ denote those whose receiver node is m. For example, referring to the node topology graph shown in Fig. 3(a), $\mathcal{F}_t(3) = \{f_4, f_5\}$ and $\mathcal{F}_r(3) = \{f_1\}$.

The flow interference graph models the set $\mathcal{F}$ of all flows in the network as a directed graph $H = (\mathcal{F}, \mathcal{E})$ where $\mathcal{E} \subseteq \mathcal{F} \times \mathcal{F}$. An ordered pair $(f, g) \in \mathcal{F} \times \mathcal{F}$ belongs to $\mathcal{E}$ if and only if 1) f and g do not share a node between them and 2) the transmission of flow f causes interference at the receiver of flow g. Note that if $(f, g) \in \mathcal{E}$, it does not necessary mean that $(g, f) \in \mathcal{E}$. The graph H that corresponds to the node topology graph G given in Fig. 3(a) is shown in Fig. 3(b) for illustration. For every $f \in \mathcal{F}$, we let $\mathcal{E}_r(f)$ and $\mathcal{E}_t(f)$ denote the sets of outdegree and indegree flows of f in H. That is, the receiver of every flow in $\mathcal{E}_r(f)$ interferes with the transmitter of f; while the transmitter of every flow in $\mathcal{E}_t(f)$ interferes with the receiver of flow f. Referring to the example in Fig. 3(b), $\mathcal{E}_r(f_2) = \{f_1\}$ and $\mathcal{E}_t(f_2) = \{f_1, f_3, f_5\}$.

B. Flow Data Rate Feasibility Conditions

Let W denote the link bandwidth of the wireless medium in bits per second; i.e., a maximum of τW bits a one-stream communication can attain in the interval $[0, \tau]$ seconds. Let's assume that each f in $\mathcal{F}$ flows data traffic at a rate of $x(f) \times W$ bits per second. Let $\mathbf{x} = [x(f)]_{f \in \mathcal{F}}$ be the vector, referred to as *flow rate vector*, representing the normalized data rates of all flows in $\mathcal{F}$. The flow rate vector $\mathbf{x}$ is said to be *feasible* in H if there exists a time schedule in which the rates of all flows are satisfied. Formally, $\mathbf{x}$ is feasible in H if there exists a time schedule $S = [0, \tau]$ of length $\tau > 0$ in which every flow $f \in \mathcal{F}$ communicates $\tau \times x(f) \times W$ bits.

It is important to mention that there are two types of constraints that affect the feasibility of a flow rate vector. The first type of constraints is that typically resulting from interference. As already mentioned, due to interference, nodes cannot have more communications in their vicinity than what their degrees of freedom allow. The second type of constraints is due to nodes' radio capabilities; e.g., a node cannot receive and transmit at the same time. For example, referring to the node topology graph shown in Fig. 3(a), observe that even when node 4 has two transmit and two receive degrees of freedom (which would allow two concurrent flows in its vicinity), flows f_5 and f_6 cannot be active simultaneously due to node 4's radio restriction. In this paper, however, a node is allowed to transmit multiple streams each going toward different receivers as long as its transmit degrees of freedom allow it. Likewise, a node is allowed to receive multiple streams each coming from a different transmitter as long as its receive degrees of freedom allow it. The following theorem states a necessary condition on rate feasibility that is due to the radio limitation.

Theorem 2: A flow rate vector $\mathbf{x} = [x(f)]_{f \in \mathcal{F}}$ is feasible in H only if $\forall\, m \in \mathcal{N}$,

$$\sum_{f \in \mathcal{F}_t(m)} \frac{x(f)}{M_t(f)} + \sum_{f \in \mathcal{F}_r(m)} \frac{x(f)}{M_r(f)} \leq 1$$

PROOF: The proof is not included due to space limitation.■

In the remainder of this paper, a vector $\mathbf{x} = [x(f)]_{f \in \mathcal{F}}$ in H is considered to be a flow rate vector if it satisfies the radio conditions stated by Theorem 2. We now focus on deriving sufficient conditions under which flow rate vectors are feasible.

Theorem 3: $\mathbf{x} = [x(f)]_{f \in \mathcal{F}}$ is feasible in H if $\forall\, f \in \mathcal{F}$,

$$x(f) \leq \max\left\{ \frac{M_t(f)}{|\mathcal{E}_r(f)| + 1}, M_t(f) - \sum_{g \in \mathcal{E}_r(f)} x(g) \right\},$$

and

$$x(f) \le \max\left\{\frac{M_r(f)}{|\mathcal{E}_t(f)|+1}, M_r(f) - \sum_{g\in\mathcal{E}_t(f)} x(g)\right\}.$$

PROOF: The proof is not included due to space limitation.■

C. A Link-Bandwidth Calculation Mechanism

We now use the conditions of Theorem 3 to propose a distributive, link-bandwidth calculation mechanism that provides every wireless node with the capability of determining the available bandwidth between it and each of its neighbors. This mechanism is used in Section V to extend AODV [18] to support end-to-end flows with QoS requirements. We propose that each node m maintains a *Flow Contention Table* with as many entries as m's neighbors. Let $m.\mathcal{N}$ denote the set of m's neighbors. An entry of the Flow Contention Table of node m corresponding to a neighbor node $n \in m.\mathcal{N}$ should contain the following fields:

- $m.\kappa(n)$: The number of neighbors of n. This field is needed to compute $m.M_t(n)$ as described later and is sent by n. That is, $m.\kappa(n) = |n.\mathcal{N}|$;
- $m.M_t(n)$: The available transmit degrees of freedom at m to transmit to n (computed using Eq. (4));
- $m.M_r(n)$: The receive degrees of freedom that are available at m to receive from n. It is computed using Eq. (3) and the information in the field $m.\kappa(n)$;
- $m.x_t(n)$: The rate of the current flow transmitted from m to n;
- $m.x_r(n)$: The rate of the current flow received by m and transmitted by n; i.e., $m.x_r(n) = n.x_t(m)$;
- $m.x_t$: The sum rate of all flows whose transmitter is m; i.e., $m.x_t = \sum_{k\in m.\mathcal{N}} m.x_t(k)$;
- $m.x_r$: The sum rate of all flows whose receiver is m; i.e., $m.x_r = \sum_{k\in m.\mathcal{N}} m.x_r(k)$;
- $m.y_t(n)$: The sum rate of all flows whose transmitter is n; i.e., $m.y_t(n) = n.x_t$; This field is sent by n;
- $m.y_r(n)$: The sum rate of all flows whose receiver is n; i.e., $m.y_r(n) = n.x_r$; This field is sent by n;
- $m.\kappa_t$: The number of nodes that are neighbors of m and have flows to transmit;
- $m.\kappa_r$: The number of nodes that are neighbors of m and have flows to receive;
- $m.r_t(n)$: The available rate that can be transmitted by m to n without violating the radio constraints as provided by Theorem 2; $m.r_t(n) = m.M_t(n)\{1 - \sum_{k\in m.\mathcal{N}}(\frac{m.x_t(k)}{m.M_t(k)} + \frac{m.x_r(k)}{m.M_r(k)})\}$;
- $m.r_r(n)$: The available rate that can be received by m from n without violating the radio constraints as provided by Theorem 2; $m.r_r(n) = m.M_r(n)\{1 - \sum_{k\in m.\mathcal{N}}(\frac{m.x_t(k)}{m.M_t(k)} + \frac{m.x_r(k)}{m.M_r(k)})\}$;
- $m.c_t(n)$: The available rate that can be transmitted by m to n while satisfying the sufficient conditions provided by Theorem 3; $m.c_t(n) = \max\{\frac{m.M_t(n)}{m.\kappa_r+1}, m.M_t(n) + m.x_t - \sum_{k\in m.\mathcal{N}} m.y_r(k)\}$;
- $m.c_r(n)$: The available rate that can be received by m from n while satisfying the sufficient conditions provided by Theorem 3; $m.c_r(n) = \max\{\frac{m.M_r(n)}{m.\kappa_t+1}, m.M_r(n) + m.x_r - \sum_{k\in m.\mathcal{N}} m.y_t(k)\}$;
- $m.a_t(n)$: The available rate that node m can transmit to node n; $m.a_t(n) = \min\{m.r_t(n), m.c_t(n)\}$.
- $m.a_r(n)$: The available rate that node m can receive from node n; $m.a_r(n) = \min\{m.r_r(n), m.c_r(n)\}$.

A node can rely on its Flow Contention Table to decide whether to accept a new flow destined to one of its neighbors. We assume that new flows are always requested through (or initiated by) the transmitter of the flow. If the rate of the new flow is greater than the available rate that a node can transmit, then the request for a new flow is denied. When the transmitter's Flow Contention Table indicates an available bandwidth greater than the requested rate, the transmitter then sends a special message (flow request message) to the receiver. Only when both the transmitter and the receiver have enough bandwidth, can the flow be admitted.

The available rate that a node can transmit or receive over a link depends on several factors such as 1) the channel conditions and power availability; 2) the number of neighbors having flows to carry; and 3) the rates of the interfering flows. These factors are dynamic and hence change over time. Each node constructs and updates its Flow Contention Table distributively based on an exchange of messages between it and each of its neighbors. Whenever there is a relevant change in its Flow Contention Table (such as a new flow has emerged, a flow has finished, etc), a node must broadcast an update to all its neighbors. Each Flow Contention Table field can be updated either by the node itself (e.g., $m.x_t$), or via receiving it from the appropriate neighbor (e.g., $m.\kappa(n)$). Fields that should be sent by the node's neighbors are indicated in the above itemized description of the Flow Contention Table.

It is worth mentioning that the complexity of the proposed mechanism in terms of message overhead is minimum for three reasons. First, the mechanism is distributive; i.e., each node requires information exchange with its immediate neighbors only to build its Flow Contention Table. Second, most of the entries are computable based on local information; i.e., no need for exchanging control messages with neighbors. Third, even those entries that must be sent by a node's neighbors can be sent along with those control messages that the underlying MAC protocol needs to exchange anyway. For example, NULLHOC [1] requires that nodes exchange their transmitting/receiving weight vectors to their neighbors prior to establishing their communications. Hence, the admission control messages could be sent along with NULLHOC's control messages. In terms of memory space, the complexity of the mechanism is also minimum, again, due to its distributive feature. Nodes are required to keep track of their immediate neighbors' information only. As for the complexity in terms of the time required to find routes, it is that of the underlying routing protocol since our mechanism relies on existing end-to-end routing protocols such as AODV [18] to operate.

It is important to reiterate that this paper does not propose a MAC protocol. Instead, we propose an admission control mechanism that relies on 1) underlying MAC protocols to exchange its messages, and 2) existing routing protocols to find QoS aware routes for end-to-end flows. Here, we use NULLHOC [1] and AODV [18] as the underlying MAC and routing protocols.

TABLE II
SIMULATION PARAMETERS

sym.	Description	Value
N	number of the wireless nodes	50
A	size of the cell	100×100 m^2
d	range of the signal's transmission	20 m
K	size of the antenna arrays	8
W	capacity of the wireless medium	54 Mbps
R	average of the end-to-end flow data rates	$3\%W$ Mpbs
ξ	tolerable frame error rate	3%

V. PERFORMANCE EVALUATION

In this section, we evaluate the performance of the proposed admission control mechanism by 1) studying its end-to-end flow acceptance capability and 2) determining its network throughput utilization. The evaluation is carried out via intensive simulations each of which is run until the measured metrics converge to within 1% of the real value at a confidence level of 98%.

A. Simulation Method

We simulate random wireless ad-hoc networks each consisting of N nodes. The capacity of the medium, W, is defined as the maximum number of bits that a one-antenna equipped node can transmit in one second. Nodes are uniformally distributed in a cell of size A meters square where two nodes are considered neighbors if the distance between them does not exceed d meters. Each node is equipped with a K antenna array and associated with a maximum normalized power selected from a uniform distribution in the range $[0.8\bar{P}, 1.2\bar{P}]$ where $\bar{P}$ is the average of the maximum normalized powers. During the course of simulations, end-to-end flows are generated randomly according to a Poisson process with arrival rate λ. Each end-to-end flow is characterized by 1) a random pair (source – destination) of nodes; 2) a chain of one-hop flows constituting the shortest path between these two nodes; 3) a flow data rate selected from a uniform distribution in the range $[0.8\bar{R}, 1.2\bar{R}]$ where $\bar{R}$ is the average of the data rates; and 4) an exponentially distributed duration of rate μ. We define $\eta = \frac{\lambda}{\mu}$ to be the *network load*. Simulation parameters are summarized in Table II.

B. End-to-End Flow Acceptance Capability

First, we study the effect of the network load η on the end-to-end flow acceptance capability of the admission control mechanism. To do so, we measure the *flow blocking probability B_p* of end-to-end flows during simulations. When a new end-to-end flow arrives, the flow is admitted to the network only if all flows (previously and newly accepted flows) satisfy the conditions stated by the admission control mechanism.

Figs. 4 and 5 show B_p as a function of the network load η respectively for different values of the maximum normalized powers and the channel estimation error variances. Note that, as expected, when the maximum transmit powers increase or the variances of the channel estimation errors decrease, the end-to-end flow blocking probability of the admission control mechanism decreases and hence the flow acceptance rate increases. Given the network load η, the average maximum normalized power $\bar{P}$, and the channel estimation error variance σ_E^2, the figures also allow to determine the number of admitted and currently active end-to-end flows in the network. For example, when $\eta = 200$, $\bar{P} = 40$ dB, and $\sigma_E^2 = 10^{-3}$, then $B_p \approx 0.25$ and hence the number of end-to-end flows currently admitted into the network is about $(1 - B_p) \times \eta = 150$.

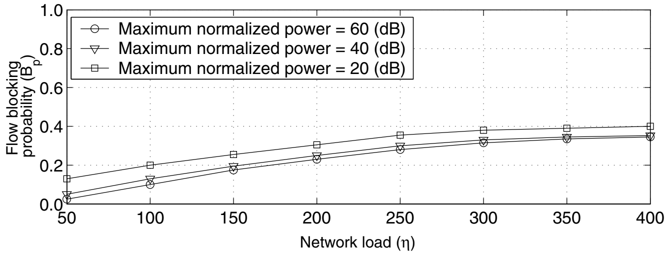


Fig. 4. Effect of the network load η on the flow blocking probability B_p when $\sigma_E^2 = 0$ and $\bar{P} = 20$, $\bar{P} = 40$, and $\bar{P} = 60$ dB: confidence level $= 98\%$, and confidence interval $= 1\%$.

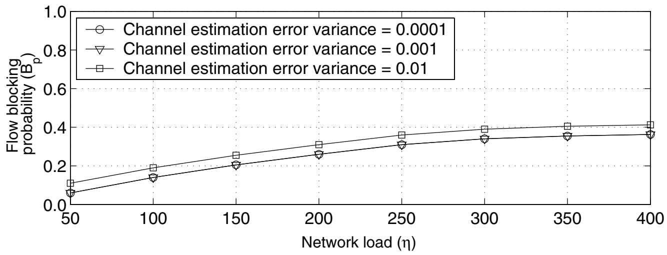


Fig. 5. Effect of the network load η on the flow blocking probability B_p when $\bar{P} = 40$ dB and $\sigma_E^2 = 10^{-4}$, $\sigma_E^2 = 10^{-3}$, and $\sigma_E^2 = 10^{-2}$: confidence level $= 98\%$, and confidence interval $= 1\%$.

C. Network Throughput Utilization

In Section V-B, we evaluated the flow acceptance capability of the admission control mechanism in terms of the number of admitted and currently active flows in the network. In this section, we would like to know how much of the total network throughput those admitted and currently active flows utilize? To answer this question, we define two metrics, *Actual Total Bit Meter Per Second* ($\mathcal{U}$) and *Upper Bound Total Bit Meter Per Second* ($\hat{\mathcal{U}}$), as $\mathcal{U} = \frac{\sum_{f \in \mathcal{F}_{all}} R_f \times D_f \times L_f}{T}$ and $\hat{\mathcal{U}} = \frac{A}{\pi d^2} \times K \times W \times \bar{h}$ and measure them during the course of simulations. $\mathcal{F}_{all}$ is the set of all admitted end-to-end flows; R_f, D_f, and L_f are respectively the rate in bits per second, the duration in seconds, and the length in meters of the end-to-end multi-hop flow f; T is the total simulation time in seconds; and $\bar{h}$ is the average hop length in meters. We define the *normalized network throughput utilization* (ρ) to be $\rho = \mathcal{U}/\hat{\mathcal{U}}$. The idea here is that, during a one-second period, a cell could at most have $\frac{A}{\pi d^2}$ concurrent communications (spatial reuse) each of which could at most deliver $K \times W$ bits[2] over a distance of $\bar{h}$ meters. Clearly, in practice, the upper bound $\hat{\mathcal{U}}$ cannot be achieved due to: 1) the limitation of transmit powers; 2) the errors associated with channel estimation methods; 3)

[2]This corresponds to when: 1) all antenna elements are used for spatial multiplexing; 2) there is no power limitation; and 3) the channel estimation method is perfect.

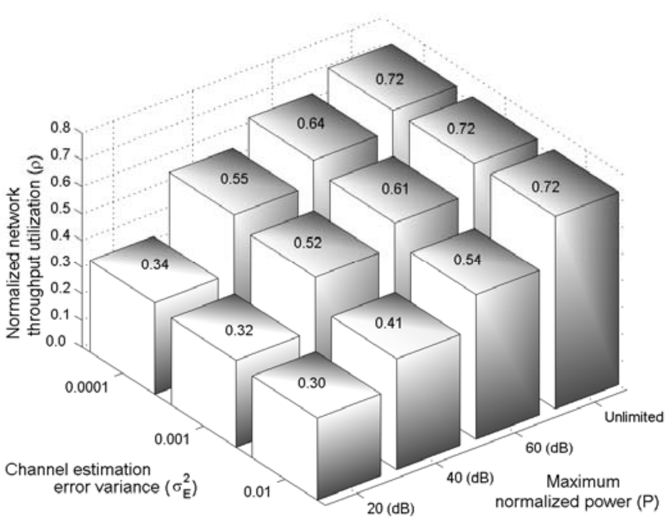


Fig. 6. Normalized network throughput utilization (ρ) for network load $\eta = 400$: confidence level $= 98\%$, confidence interval $= 1\%$.

the possibility of having some portion of the cell empty of nodes—unbalanced distribution of the nodes over the cell; and 4) the possibility of having some nodes not forwarding data—unbalanced distribution of the flows' data rates over the nodes. The upper bound is, however, used as a baseline for measuring the network throughput utilization obtained under the proposed admission control mechanism.

It is important to reiterate that the developed admission control theory has two key features that one needs to evaluate separately. First, since the mechanism relies on the derived sufficient conditions (stated by Theorem 3) to admit/reject flows, it is then worth determining how conservative the mechanism is due to the sufficiency of these conditions. Second, even when the conditions are also necessary, physical limitations such as power limitation and errors of channel estimation methods are also expected to degrade the performance of the network. Hence it is also worth studying the effectiveness of the proposed admission control mechanism in the presence of these physical limitations.

To determine how conservative the proposed sufficient conditions are without considering the impact of physical limitations, we first run simulations during which the maximum transmit power constraint of all nodes is relaxed (unlimited power $\bar{P}$ for each node). We then simulate for different combinations of maximum normalized powers and channel estimation errors to study the impact of physical limitations on the effectiveness of the admission control mechanism. The impact of the sufficiency of the conditions as well as that of the physical limitations on the network performance is evaluated in terms of the achievable normalized network throughput utilization ρ.

Fig. 6 shows the normalized network throughput utilization ρ for a network load of $\eta = 400$. Each bar corresponds to a combination of a maximum normalized power $\bar{P}$ and a channel estimation error variance σ_E^2. Note that when the power constraints are relaxed ($\bar{P}$ is unlimited), our proposed sufficient conditions result in a normalized network throughput utilization of 0.72. Hence the proved sufficient conditions perform well since, as mentioned earlier, the upper bound $\hat{\mathcal{U}}$ (with which the measured network throughput $\mathcal{U}$ is compared) is practically unattainable. (To the best of our knowledge, admission control methods for wireless ad-hoc networks using multiple antennas have not been developed yet and hence we only can evaluate/compare our method with respect to an upper bound.) The figure also illustrates that the network throughput utilization decreases as the maximum transmit power decreases or as the variance of the channel estimation errors increases. For example, when $\bar{P} = 40$ dB and $\sigma_E^2 = 10^{-3}$, the normalized network throughput utilization is $\rho = 0.52$. In essence, the figure shows that for reasonable values of the physical parameters, the admission control mechanism results in high network throughput utilizations.

VI. Conclusion

This paper develops an admission control theoretical framework that exploits the benefits of multiple antennas to better support applications with QoS needs in wireless ad-hoc networks. The developed theory provides wireless ad-hoc networks with flow-level admission control capabilities while accounting for cross-layer effects between the PHY and the MAC layers. First, we develop a packet-level statistical framework that models the spatial reuse and the spatial multiplexing benefits offered by the array of antennas. Second, we use the proposed packet-level statistical method to develop a flow-level admission control theory. Through simulations, we show that the proposed theory results in high end-to-end flow acceptance rates and network throughput utilizations. We also demonstrate the importance and the effect of considering cross-layer couplings into the development of admission control methods.

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