Contention in Multi-hop Wireless Networks: Model and Fairness Analysis

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ABSTRACT

In multi-hop wireless networks with Carrier Sense Multiple Access (CSMA), unfairness may arise due to a number of reasons. A majority of the existing work focuses on fairness issues due to hidden terminals and the impact on backoff mechanisms. This paper focuses on the unfairness arising due to unequal contention opportunities at a node; some nodes rarely observe an idle channel since two or more interferers that are not in range with each other can transmit together. Contention unfairness is unrelated to hidden terminals. In order to understand the impact of contention and gain insight into developing solutions for contention unfairness, we develop a model from first principles for contention in IEEE 802.11 networks. The accuracy of the model is validated through simulations and the results show that such unfairness is a common phenomenon. Based on the insights gained from the model, we propose and evaluate a distributed scheme that reduces the effect of unfairness due to contention. Simulation results show that the proposed scheme achieves an average improvement of 25% in fairness, with a small reduction in overall throughput.

Categories and Subject Descriptors

C.2.2 [**COMPUTER-COMMUNICATION NETWORKS**]: Network protocols

General Terms

Algorithms, Experimentation, Measurement, Performance

Keywords

Wireless, MAC, CSMA, Interference, Fairness

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1. INTRODUCTION

Multi-hop wireless networks (MHWNs), such as sensor networks and mesh networks, are increasingly used in a variety of applications to provide network access with minimum infrastructure demands. In MHWNs, nearby nodes share a common wireless channel, causing interference to each other. The nature of the wireless medium makes effective and fair arbitration of this shared medium a difficult task.

Carrier Sense Multiple Access (CSMA) protocols are widely used as MAC protocols in these networks since they operate without central coordination, and adapt to the dynamics of traffic and mobility in MHWNs. However, performance of CSMA protocols in MHWNs is inefficient. Detrimental interactions like such as hidden [20] and exposed terminals [4] arise even in advanced CSMA protocols such as IEEE 802.11 [18]. Such interactions give rise to severe performance degradation and unfairness, and these effects are well-studied in the existing literature [4, 3, 1].

The paper focusses on a more fundamental form unfairness due to collective interaction between the nodes. The shared nature of the wireless channel causes different nodes to perceive different channel states (busy or idle). This asymmetry in the channel view lead to unfair contention opportunities at certain nodes. Consider an illustrative scenario where a node A is interfered with by two or more nodes $(B, C, \ldots)$ such that the interfering nodes are themselves out of sensing range with each other. The interferer's transmissions overlap in time and, hence, the channel is idle at A only when *all its interferers are idle*. This leads to a low probability for channel access opportunities for A and it suffers from long-term and potentially severe unfairness. We call this problem *contention unfairness*, and it occurs even in the absence of hidden terminals.

Characterizing the interaction pattern and the implications of contention unfairness is a challenging problem. Contention unfairness has not received significant attention in fairness literature, where the focus is often on hidden terminals and the impact of exponential backoff [8, 3]. Earlier studies have proposed models for general CSMA protocols [5] and, more recently, for IEEE 802.11 [22, 8]. A majority of these models use balance equations or iterative approach to solve the problem. This hides the details of the underlying processes that cause the behavior. Second, they offer little insight into how to go about addressing the problem.

The third drawback of these models is that they do not consider the important protocol parameters.

The first contribution of this paper is a throughput model of contention that provides insight into the processes that lead to poor contention. Our model differs from the existing ones in the following ways: (1) we identify and characterize the primary parameters of contention and fairness, such as the distribution of the idle-channel times seen at the nodes. The characteristics of these parameters provide invaluable insight into interaction patterns in MHWNs and, as we show in Section 5, are effective in designing distributed protocols for avoiding coordination inaccuracies; (2) we consider detailed IEEE 802.11 protocol rules. Ignoring these parameters leads to significant error in performance metrics: e.g., ignoring the effect of DCF Interframe Space (DIFS) parameter underestimates channel idle periods by around 30% in networks with dense traffic; and (3) our model provides a low-complexity solution for performance prediction which enables real-time online use of the model in network testbeds and simulations.

The second contribution of the paper is a distributed protocol that mitigates the impact of contention unfairness. Based on the insights obtained from the model, the nodes exchange *contention information* and adjust their backoff windows accordingly. This mechanism is different from the existing adaptive backoff approaches which are primarily focused on reducing the effect of packet collisions on network performance [4, 11, 1, 7]. In fact, we argue in Section 6 that a majority of such mechanisms have an adverse effect on contention unfairness. The proposed mechanism has a negligible overhead and improves the fairness by approximately 25% in random networks.

The remainder of the paper is organized as follows: Section 2 describes the background and illustrates the impact of contention unfairness in CSMA networks through a simple example. The throughput model is explained in Section 3 and validated in Section 4. Section 5 describes the distributed mechanism to mitigate the contention unfairness. Section 6 discusses the related work. Finally, conclusions and the future work are described in Section 7.

2. BACKGROUND AND MOTIVATION

A primary task in developing throughput models of MHWN is to represent the interactions between the nodes and the way in which contend. Precise computation of the effect of interactions and its effect on performance are computed later. In this section, we briefly describe the IEEE 802.11 protocol and then explain the framework for representing interactions in CSMA protocols. Finally, we utilize this representation mechanism to illustrate the impact of contention unfairness with a motivating example.

2.1 IEEE 802.11

One of the most widely used CSMA MAC protocol in today's wireless networks is IEEE 802.11 [18]. Under CSMA protocols, the sender does not transmit the data when the channel is sensed busy. In addition, the source also employs additional collision avoidance (CA) mechanisms. The source node that is ready to transmit a packet will pick a *backoff value* which is uniformly distributed between $[0, \mathrm{CW}_{\min}]$ and waits for an idle channel. If the channel is idle for DIFS period, the node starts decrementing its backoff value. The DATA packet is transmitted once the backoff value reaches zero. If the channel becomes busy while decrementing, the node pauses its backoff and resumes once the channel appears idle for DIFS period. If the source fails to get the ACK packet, it assumes a packet collision and doubles the backoff window (Binary Exponential Backoff or BEB). In the RTS-CTS mode of IEEE 802.11, the source and destination observes a 4-way handshake to avoid collision. However, even such schemes are prone to unsuccessful handshakes.

2.2 Representing interactions

Representing the various, and possibly uncoordinated, interactions play an important role in modeling the MHWN. We follow the concept of Independent Sets from graph theory to represent the set of links that interact at a given point of time. This is one of the standard approaches that is followed by throughput models in MHWNs [5, 8].

In order to represent the interactions in IEEE 802.11, we first determine the set of links that interact with each other. We determine the links that are allowed to initiate transmissions concurrently under the protocol rules. A set of links can be active at the same time when each source cannot sense the transmission of other sources (otherwise the CSMA protocol prevents transmission). A group of such links whose sources can transmit together is henceforth referred to as *Independent Contention Set (ICS)* of links.

Under saturated traffic, where the impact of unfairness is severe, all the sources are greedy and hence a maximum number of concurrent links can be active. We represent the set of such maximum concurrent links by *Maximal ICS (MICS)*. MICS provides a natural abstraction to represent the state of the wireless channel by listing the links that are active at any given time and many existing CSMA models use the independent set approach to estimate the performance of the network [5, 22]. The problem of finding MICS is similar to the graph theory problem of finding the *maximal independent sets* in a *Conflict Graph* [23]: a graph where each link is represented as a vertex and an edge exists between two vertices if the corresponding source nodes interfere with each other. While computation of maximal independent sets is NP-hard, there exist several reasonable approximation algorithms [10].

We now explain the basic notations used in the model. In a MHWN with N nodes, let L be the set of active one-hop links and s_i, r_i denote the source and receiver for link i, respectively. Let $M = \{M_1, M_2, \ldots, M_n\}$ be the set of MICS for a given network scenario. As different links contend for the channel and transmit packets, the set of active links in the network changes. In other words, the channel state shifts from one MICS (or ICS) to another. Hence, changes in the channel states are represented as transitions between the MICS. The *difference set* of two MICS is denoted by $\mathcal{D}_{ab} = M_a - M_b$. A transition from MICS M_a to MICS M_b will occur when the links in the set $\mathcal{D}_{ab}$ are idle and the links in the set $\mathcal{D}_{ba}$ become active.

2.3 Flow in the middle

We now describe the contention in MHWNs through a simple and representative example. We use this example to motivate the importance of contention fairness, demonstrate the model construction and evaluate the effectiveness of the proposed adaptive scheme. It should be noted that we use this example for its simplicity in showing the effect of contention fairness, but the proposed model is generic and can be applied to any reasonably static MHWN.

Figure 1 shows the "Flow-in-the-Middle (FIM)" scenario that demonstrates the contention unfairness in MHWNs. Three active links *A*, *B* and *C* are present such that links *A* and *C* can transmit concurrently while *B* can transmit only when neither *A* nor *C* is active (because of the busy channel from *A* and/or *C*). Consequently, we define the set of MICS $M = \{M_1, M_2\}$ with two MICS $M_1 = \{A, C\}$ and $M_2 = \{B\}$. In this example, in spite of the absence of the hidden terminals, *B* faces an acute contention unfairness due to a constant busy channel by the overlapping transmissions of *A* and *C*.

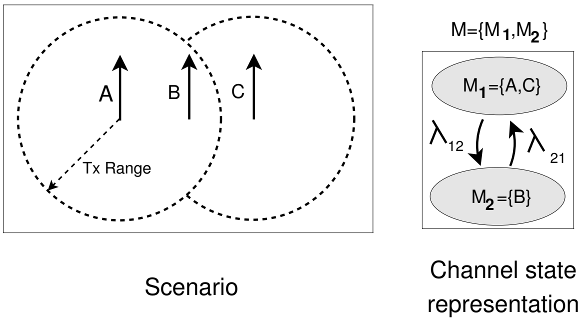


Figure 1: Flow in the Middle: Representative example for contention unfairness

3. THROUGHPUT MODEL

In this section, we analyze the contention unfairness in a MHWN and propose a throughput computation model. The model accounts for contention by first identifying sets of nodes that are allowed to transmit concurrently by the protocol rules. Based on these sets, we derive (1) the probability of observing an idle-channel; and (2) the distribution of the periods of idle-channel. We estimate the throughput and fairness metrics by applying the protocol specific rules to the above two parameters.

3.1 Assumptions

As a representative CSMA protocol, we model the contention unfairness of IEEE 802.11 protocol, both under *basic mode* and RTS-CTS mode. In order to focus on the parameters that affect contention unfairness and to isolate its causes, we consider network with no hidden terminals. While such an assumption limits the applicability of the model in a general MHWN, it enables isolating the effect of contention unfairness. Moreover, the contention fairness model provides a basic framework to compute the effect of hidden terminals. The impact of hidden terminals is measured after quantifying the contention effectiveness of the links involved in the collision. Extended model to handle hidden terminals is discussed in Section 3.4.

Certain protocol rules are simplified for to reduce the complexity of the model. We assume simple distributions of the backoff and packet length. The IEEE 802.11 chooses backoff value from a uniform discrete distribution between $[0, \mathrm{CW}_{\min}]$, while we assume that the source node of the link i chooses a backoff value that is exponentially distributed. We assume exponential distribution for packet sizes. While formulating the model with the uniformly distributed backoff and, say, constant packet sizes is theoretically possible, solving the model for parameter values becomes computationally infeasible. For example, a simple step of computing the distribution of idle-channel periods when a single link is transmitting should be solved by iterative numerical methods since the inverse laplace function for the combined idle-transmit cycles is unsolvable, and hence the problem is not solvable in a computationally efficient manner [21]. However, we validate the accuracy of this assumption: we show in Section 4.1 that the distribution of the channel idle-times matches closely to the IEEE 802.11 protocol. The simulation results also show that the model with this simplification matches very close to the normal IEEE 802.11 operation.

3.2 Notations and summary of the approach

Let Y_n^i denote the backoff value chosen during the n^{th} packet transmission by the link i. After the backoff is decremented, the node transmits the packet. The number of slots required for link i to successfully transmit a packet is denoted by Z_n^i where $n = 1, 2, 3, \ldots$. This includes the time for control packets like RTS, CTS and ACK. The density and distribution functions of Y are denoted by f_Y and F_Y, respectively. Similar definitions apply for f_Z and F_Z. Summarizing,

$$Y_n^i \sim \exp(\beta_i) \text{ and } Z_n^i \sim \exp(\tau_i) \tag{1}$$

We now describe the steps involved in throughput estimation. Recall that MICS can represent channel states and transition between the MICS occur when the links in one MICS are idle and the links in another MICS start transmitting. Using the rules of the IEEE 802.11 protocol, we calculate the fraction of the time each MICS is active and compute the throughput of each link. The three main steps involved are:

(1) Computing the transition rate (λ_{ab}) between a pair of MICS M_a and M_b by calculating essential parameters.

(2) Computing the long-term probability (P_a) that MICS M_a is active.

(3) Estimating the throughput of link i by using P_a and different link parameters like $CW_{\min}$ and packet length.

Step 1: Rate of transition between MICS

This step is challenging since we derive the necessary parameters that enable a transition between a pair of MICS while accounting for the majority of the protocol interactions. A transition from M_a to M_b occurs when the links in $\mathcal{D}_{ba}$ start transmitting. A transmission from a link in $\mathcal{D}_{ab}$ will prohibit the transition.

A link in M_b decrements its backoff window only when the interfering links in M_a are not active and transmit the packet when the backoff value is zero. Capturing this behavior requires derivation of two important characteristics of idle-channel periods that enable a link in M_b to transmit:

(i) How often do the links in M_b observe an idle channel?

(ii) Conditioned on the channel being idle, how long does the channel remain idle? These continuous idle-channel periods that are observed at a node will henceforth be called as *Channel Gaps*.

In order to answer (i), we compute the proability that the channel is idle when a single link and a set of independent links are active. To answer (ii), we compute the distribution of the channel gaps given that a link observes an idle timeslot. This helps to account for the actions taken by a node upon observing an idle channel. Finally, we derive the rate of transition between two MICS.

3.2.1 *Channel gaps for a single active link*

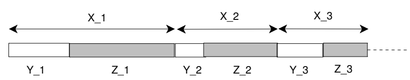


Figure 2: Transmission attempts of a link

We model the backoff and transmission periods of the link as an *Alternating Renewal Process* [13] as shown in Figure 2. Let $X_n^i = Y_n^i + Z_n^i$ denote the total number of slots taken for transmitting one packet. The density function $f(X_n^i)$ and the asymptotic probability that channel is idle at a link i (denoted by p_{LI_i}) are:

$$f_{X_n^i}(t) = \frac{\beta_i \tau_i}{\beta_i - \tau_i}\left(e^{-\tau_i t} - e^{-\beta_i t}\right), \tag{2}$$

$$p_{\mathrm{LI}_i} = \frac{E[Y(i)]}{E[X(i)]} = \frac{\tau_i}{\beta_i + \tau_i}. \tag{3}$$

Similarly, let p_{LS_i} be the probability that source of the link i will *start* transmitting the packet at a given timeslot. This corresponds to one slot for each renewal cycle. Hence,

$$p_{\mathrm{LS}_i} = \frac{1}{E[X(i)]} = \frac{\beta_i \tau_i}{\beta_i + \tau_i} \; . \tag{4}$$

3.2.2 Channel gaps for a set of active links

In the previous paragraph, we calculated the probability of a link *becoming* or *being* idle when there are no other interfering links. We now view the problem with respect to the link that is observing a busy-channel due to a set of interfering links. We calculate the probability that the link observes an idle-channel and derive the distribution of the channel gaps.

Probability that channel becomes idle.
Let $I(j,a)$ denote all the independent links (i.e. links that do not interfere with each other) that interfere with the link j. Such set of independent links can be a subset of links in MICS M_a. Using p_{LS_i} and p_{LI_i} for all the links i in $I(j,a)$, the probability that the channel *first becomes idle at link j* (denoted by $p_{\mathrm{ci}}(I(j,a))$) is given by

$$p_{\mathrm{ci}}(I(j,a)) \quad = \quad p(1) - p(2) + p(3) - \dots \; , \tag{5}$$

where $p(m)$ denotes the probability that m links in $I(j,a)$ become idle at a given time slot and the remaining links are idle. Using these values for all the links in $I(j,a)$, we can calculate the value of $p_{\mathrm{ci}}(I(j,a))$. The value of $p(m)$ can be computed from p_{LS_i} and p_{LI_i}. For example $p(1) = \sum_{i \in I(j,a)} (p_{\mathrm{LS}_i} \prod_{j \in I(j,a), j \neq i} p_{\mathrm{LI}_j})$. Note that since p_{LS} and p_{LI} are asymptotic probabilities, p_{ci} is an asymptotic probability that the channel is idle.

Channel gap distribution.
In the previous paragraph, we calculated the probability that the channel *becomes* idle at a given link. We now compute the distribution of the channel gap *given that the channel is idle*.

Consider a set of independent links I. Each link $k \in I$ chooses a backoff value from $\exp(\beta_k)$. Owing to the memoryless property of the exponential distribution, the probability that the link k will be idle for a time t is independent of when it started its backoff procedure. The length of the *collective channel gap* (G), where all the links in I are inactive, is the minimum of the backoff values chosen by links in I (competing exponential random variables). Hence,

$$G(I) \sim \exp(\phi_I) \quad \text{, where} \quad \phi_I = \sum_{k \in I} \beta_k \; . \tag{6}$$

We now derive the channel gap for link i when the set of independent links $I(i,a)$ create a busy-channel at i. Given that link i has just observed a channel gap after the links in $I(i,a)$ have become idle, the length of the collective channel gap of the set $I(i,a)$ is given by the distribution $G(I(i,a))$ (see Equation 6). For simplicity, we denote this by $G(I)$ if the context of the link and MICS M_a is obvious.

The procedure to decrement the backoff is started only after the channel is observed idle for DIFS duration. Hence, if the $G(I)$ has a large ϕ_I, then the link starts the backoff procedure with a very small probability: an indication of severe starvation. In the FIM example of Figure 1, the model and simulation results indicate that, in addition to long wait time to observe an idle-channel, around 30% of the channel gaps are lesser than DIFS at the the source of link B. It should be noted that existing related work [22] do not explicitly capture such behavior.

The probability that the length of the channel gap is greater than DIFS (denoted by $p_D(G(I))$) can be directly obtained from the distribution of $G(I)$. We have

$$p_D\big(G(I)\big) = e^{-\phi_I \, \mathrm{DIFS}} \; , \tag{7}$$

where DIFS represents the number of slots required to complete a DIFS period.

3.2.3 Expected wait time until a link starts decrementing backoff

In the previous paragraph, we had derived the distribution of channel gaps conditioned on the channel being idle. We now compute the unconditioned expected value of the time (in number of slots) that the node has to wait in order to *start decrementing its backoff*. We first compute the expected value of the time slots needed to start decrementing the backoff and then compute the overall expected time for a link to transmit a packet.

Recall that $p_{\mathrm{ci}}(I)$ is the probability that the channel *becomes* idle at a particular time slot given that it was busy in the previous time slot. Hence, the number of slots to wait before we observe an idle channel is geometrically distributed with a success probability $p_{\mathrm{ci}}(I)$ and its expected value is given by

$$E[\text{\# slots to observe idle channel at } i] = \frac{1}{p_{\mathrm{ci}}(I)} \; . \tag{8}$$

Given that $p_D(G(I))$ denotes the probability that the channel gap is greater than DIFS, the expected number of slots for link i to start decrementing backoff value is given by

$$E[W_s(i)] = \frac{E[\text{\# slots to observe idle channel at } i]}{p_D(G(I))} \; . \tag{9}$$

The expected number of backoff slots decremented at each channel gap can be directly calculated from the gap distribution $G(I(i,a))$ (say, $E[W_d(i)]$). Using this value and Equation 9, we can calculate the overall number of slots that the source of link i has to wait to decrement an average backoff value of $\frac{1}{\beta_i}$ and start transmitting (denoted by $E[W_t(i)]$). We obtain

$$E[W_t(i)] = \frac{E[W_s(i)] + E[W_d(i)]}{\beta_i E[W_d(i)]} \; . \tag{10}$$

3.2.4 Transition rate between MICS

We now derive the final step for computing the transition rates. Recall that a transition from MICS M_a to MICS M_b occurs only when all the links that in the set $\mathcal{D}_{ab}$ stop transmitting and the links in $\mathcal{D}_{ba}$ start transmitting.

The transition from M_a to M_b is observed if any of the links in $\mathcal{D}_{ba}$ starts its transmission. Similarly, any link in $\mathcal{D}_{ab}$ will prohibit this transition. Hence, we have to now compute the minimum backoff window chosen by the difference sets $\mathcal{D}_{ab}$ and $\mathcal{D}_{ba}$. Given that all the links choose the backoff values from their respective exponential distributions, the minimum backoff will be a competing exponential variable among the links in a difference set (similar to Equation 6). This enables the computation of transition probability by abstracting it at two virtual links with backoff values chosen from exponential distributions $G(\mathcal{D}_{ab})$ and $G(\mathcal{D}_{ba})$ (computed from Equation 6). Given the exponential nature of $G(\mathcal{D}_{ab})$ and $G(\mathcal{D}_{ba})$, the probability that of transition from M_a to M_b is given by

$$P(\text{Transition from } M_a \text{ to } M_b) = \frac{\phi_{\mathcal{D}_{ab}}}{\phi_{\mathcal{D}_{ab}} + \phi_{\mathcal{D}_{ba}}} \; . \tag{11}$$

Using Equation 11, we can now compute the expected time for transition from M_a to M_b. We note that even a single link activation in M_b is going to enable transition from M_a to M_b. Hence, we use the minimum value of $E[W_t(i)]$ for all the links i in M_b and obtain

$$E[\text{Time required for transition from } M_a \text{ to } M_b] = \frac{\min(E[W_t(i)], \forall i \in M_b)}{P(\text{Transition from } M_a \text{ to } M_b)} . \quad (12)$$

The rate of transition from M_a to M_b, denoted by λ_{ab}, is given by

$$\lambda_{ab} = \frac{1}{E[\text{Time required for transition from } M_a \text{ to } M_b]} . \quad (13)$$

This completes the derivation of expected transition rates from one MICS to another and hence the throughput model.

Step 2 : Long-term probabilities of MICS

We represent the different states of the channel by active MICS. A continuous-time Markov chain is defined with a state space M, each state representing the state of the channel i.e. the active MICS. Let λ_{ab} be the rate of transition between two MICS M_a and M_b. We assume λ_{ab} to be exponentially distributed. The simulation results show that the accuracy of the model is not compromised by this assumption. The long term probability of staying at M_a (represented as P_a) can be calculated by solving the balance equations

$$P_a \sum_{b \in M, b \neq a} \lambda_{ab} = \sum_{b \neq a} P_b \lambda_{ba} \qquad , \forall a \in M \text{ and}$$
$$\sum_{a \in M} P_a = 1 . \quad (14)$$

Step 3: Calculating the throughput

After the computation of long-term probabilities for each MICS, we can derive the throughput of a link i (denoted by T_i). The fraction of time available for a link i is given by the sum of all long-term probabilities of MICS to which i belongs. The throughput is computed by determining the the efficiency factor of the link (ε_i). Here ε_i is the ratio of the time required to transmit the data payload to the time required for completing one successful transmission with the overhead of physical/MAC layer headers, DIFS, SIFS, RTS,CTS, ACK and time required for decrementing the average backoff duration. Summing up, we have

$$T_i = \varepsilon_i C \sum_{a \in M, i \in M_a} P_a . \quad (15)$$

where C represents the capacity of the channel.

The model is also easily extended to handle RTS-CTS mode of IEEE 802.11. The construction of the MICS differs slightly from basic mode where it is required to account for RTS-CTS based handshake. Overhead due to RTS-CTS packets are included while calculating the throughput. Rest of the model remains the same. In addition, the model also recognizes scenarios with *protocol hidden terminal* where the source sends an RTS but fails to get a CTS back due to busy channel at the receiver, thus resulting in an unsuccessful handshake.

3.3 Example scenario

In this section, we describe the formulation steps through a simple illustrative scenario. We demonstrate the model through the "Flow in the Middle" example (Figure 1). The rates for the backoff values (and packet transmission times) of the links A,B and C are exponentially distributed with parameters β_A, β_B and β_C (τ_A, τ_B and τ_C) respectively. MICS $M_1 = \{A, C\}$ and $M_2 = \{B\}$ and the set of all MICS $M = \{M_1, M_2\}$.

We now derive the transition rate from M_1 to M_2, denoted by λ_{12}. This is a more difficult and the interesting case than λ_{21}. The probabilities p_{LS_i} and p_{LI_i} are calculated for links A and C by Equations 3 and 4. The probability that the channel is observed idle at source of link B (s_B) at a given time slot depends upon A and C and occurs when both A and C are idle. This value $p_{\mathrm{ci}}(\{A, C\})$ is calculated by computing the probability that either A is idle and C becomes idle during this slot or vice-versa (Equation 5). The channel gap at B conditioned on the channel *becoming* idle at a given slot (denoted by $G(\{A, C\})$) can be calculated by the gap distribution in Equation 6. Node s_B decrements its backoff only when the channel gap observed is greater than DIFS. The probability of B finding the channel gap greater than DIFS, denoted by $p_D(G(\{A, C\}))$, is calculated by Equation 7. Having determined $p_{\mathrm{ci}}(\{A, C\})$ and $p_D(G(\{A, C\}))$, we can determine the expected time to wait till the source of B starts transmitting the packet, $E[W_t(B)]$, from Equation 10. Finally, the overall expected rate of transition from MICS M_1 to MICS M_2 (λ_{12}) is then calculated by Equation 13.

The expected rate of transition from MICS M_2 to MICS M_1 (λ_{21}) is similarly calculated and the limiting probabilities for occurrence of MICS M_1 and M_2 (denoted by P_1, P_2) are computed by solving Equation 14. Finally, throughput of the three links are computed by Equation 15.

3.4 Extension to account for packet timeouts

Above subsections formulated the model that captures the throughput estimation when the links do not experience packet collisions due to unsuccessful handshake. However, MHWNs with IEEE 802.11 is prone to hidden terminal problems and often suffer from packet timeouts, which are due to packet collision [9].

We observe two new problems that need to be accounted while handling packet timeouts:

(1) There are several categories of packet timeouts; each category has a unique signature of link throughput and fairness measures. We first identify the category of timeout within a MICS [14]. Then, we apply specific throughput estimation models [17] to compute the effect of timeout in each MICS.

(2) A timeout triggers binary exponential backoff, and the link observes extended silence periods before transmission. Hence, the link experiencing a timeout is active for only a fraction of the time. We account for this effect by decomposing the MICS into multiple Indepedent Contention Sets (ICS), where each ICS denotes possible set of active links considering the longer backoff of the link that experienced packet timeout. Finally, the transition probabilities between the set of ICS is computed as described in the above model.

Figure 3 describes an example scenario with hidden terminals, and the corresponding MICS representation. Consider only links in MICS-1 where EF experiences packet timeouts due to the hidden terminal G. Hence, the channel state may be in in one of the two stages: (1) all the three links are actively transmitting, but EF experiences collision; or (2) only AB and GH are transmitting, while EF is observing extended backoff due to collision. This effect is captured in the proposed framework by decomposing MICS-1 into ICS-1 and ICS-2 (Figure 3). We similarly account for a symmetric form of hidden terminal where link GH and AB create mutual packet collisions by decomposing MICS-2 into ICS-3 and ICS-4.

4. MODEL VALIDATION

In this section, we show that effect of the assumption that backoff values are chosen from an exponential distribution instead of uniform random distribution. Then, we validate the model with

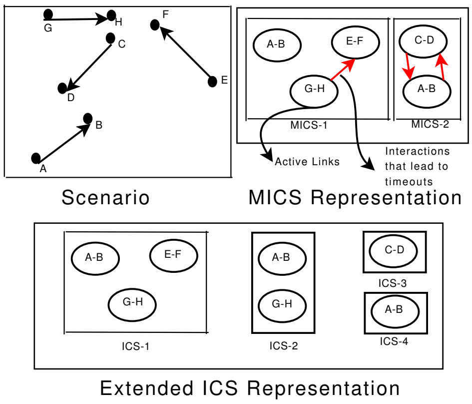


Figure 3: Extended model to handle packet timeouts

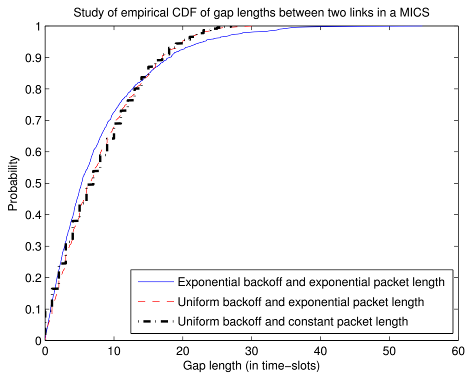


Figure 4: Numerical validation of exponential backoff assumption

simulations using Qualnet simulator [16]. Unless specified, standard 802.11 MAC parameters are assumed with 2 Mbps channel capacity. We first investigate the accuracy of the model in the FIM scenario and then consider random networks. We show that the model matches closely with simulations, even when backoff is chosen according to IEEE 802.11 standards and the packet sizes are deterministic instead of both coming from exponential distributions.

4.1 Exponential backoff assumption

In the model, the backoff values (Y_n^i) were chosen from exponential distribution instead of a discrete uniform distribution. The exponential assumption helped to simplify the model while calculating (1) the channel gap of a single link (Section 3.2.1); (2) the channel gap when multiple links are active (Section 3.2.2); and (3) Computation of the transition rates between the MICS (Section 3.2.4). In this section, we provide an insight into the complexity of the model if the backoff values were chosen according to IEEE 802.11 standards. We then present numerical results that show that the channel gap distribution under the assumption matches very closely to the distribution under IEEE 802.11.

We numerically analyze the distribution of the channel-gap lengths when two non-interfering links are active (similar to the channel gap observed by the source of the link B in the FIM example). Random backoff values are generated with mean 15.5 (corresponding to $CW_{\min} = 31$), first according to exponential distribution (as per the model) and then according to the discrete uniform distribution according to the IEEE 802.11 standards. Packet lengths were chosen from exponential distribution with the mean being 1024 bytes.

Figure 4 compares the empirical CDF of the channel gap from the two backoff distributions. It can be seen that the channel gap distribution from the two distributions are very similar, thus suggesting that our exponential backoff assumption closely approximates the IEEE 802.11 behavior. Figure 4 also shows that the channel gap distribution of our model matches the distribution for CBR traffic under IEEE 802.11, where backoff values are uniform and packet sizes are constant. This result shows it is reasonable to simplify the model by assuming exponential distribution to predict the contention unfairness in MHWNs using IEEE 802.11.

4.2 Analysis of FIM

First, the model is validated by setting same backoff parameters β for all the links. We then vary βs to observe the starvation effect in the FIM scenario. Figure 5(a) shows the FIM scenario with equal backoff parameters for all the links. We vary the packet sizes and study the throughput vs. expected backoff values. We observe that the model matches closely with the simulation. More importantly, it can be seen that there is an *acute starvation* of the link B during lower backoff values due to the unavailability of idle-channel to observe DIFS and decrement its backoff. Fairness is achieved at very high backoff values at the cost of severe throughput degradation. *This demonstrates that fair contention cannot be ensured in MHWNs by homogeneous backoff values without significant throughput reduction.*

In order to capture the effect of heterogeneous backoffs, we observe the throughput by altering the backoff parameters of sources s_A and s_C while node s_B has an expected backoff value of 15.5 slots (according to the 802.11 standard). Figure 5(b) shows the fraction of the throughput at link B. As we vary the backoff window of the s_A and s_C, the channel share for B increases. It can be seen that the model predicts the throughput of the links with a good accuracy and, more importantly, demonstrates that the judicious choice of backoff values at each node can attain overall network fairness. This motivates the development of a "Contention-aware Adaptive Backoff Scheme (CABS)", which we describe in Section 5, that alters the backoff window appropriately to attain contention fairness while maintaining an acceptable overall throughput degradation.

4.3 Random scenarios

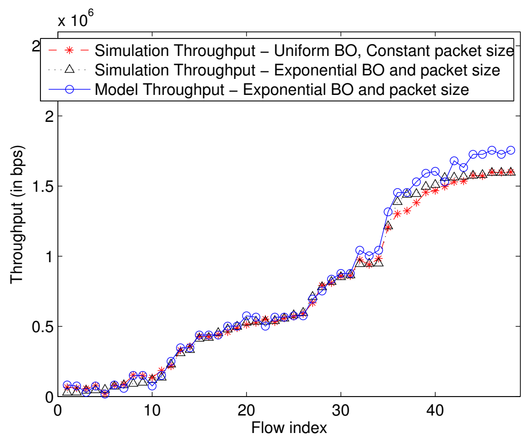
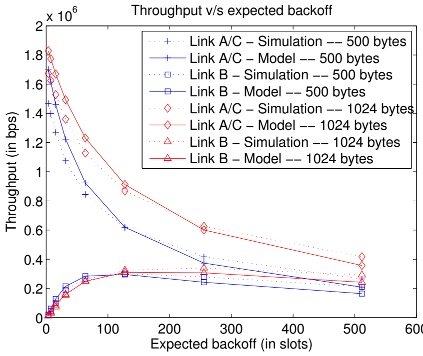
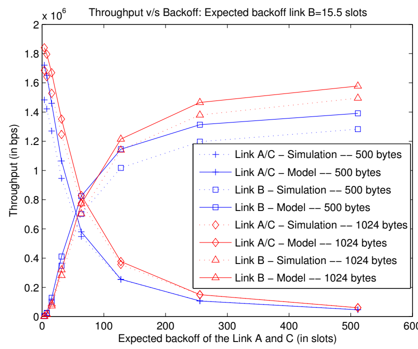


Figure 6: Validation in random scenarios

Eight random scenarios, each with 100 nodes and 6 connections,



(a) All nodes with equal backoff window. Fairness for B occurs at very high backoff values with large overall throughput degradation



(b) Vary the backoff of A and C. Fairness can be achieved with greater overall network throughput.

Figure 5: Flow in the middle: Throughput study and model validation

were chosen and IEEE 802.11 basic mode was enabled. To evaluate the effect of contention unfairness in isolation, the scenarios were selected such that there were no hidden terminals. Two types of simulations were conducted: (1) modified MAC with exponential backoff duration and packet sizes (as per our assumptions); and (2) default IEEE 802.11 with CBR traffic. Figure 6 shows the throughput of the connections in all the scenarios under IEEE 802.11 basic mode. The results show that the model accurately captures the throughput even though it assumes exponential backoff value and packet size. Similar accuracy is observed with IEEE 802.11 with RTS-CTS. The frequency and the extent of contention unfairness can be inferred from Figure 6 where a significant number of connections experience highly unfair throughput.

5. CONTENTION-AWARE ADAPTIVE BACKOFF SCHEME

In this section, we use the insights gained from the analysis and modeling of contention unfairness to develop a distributed mechanism for altering $\mathrm{CW}_{\min}$ to overcome unfairness. Henceforth, we refer to this adaptive backoff mechanism as *Contention-aware Adaptive Backoff Scheme* (CABS). While this protocol is not a feasible extension for the older device drivers of the wireless cards, recent advanced drivers and chipsets such as Atheros ath5k driver [2] and Software defined radios allow flexibility in adjusting the low level MAC parameters like $\mathrm{CW}_{\min}$.

5.1 CABS algorithm

The main idea of CABS is to track the channel busy times and modify the $\mathrm{CW}_{\min}$ at the source nodes accordingly. Recall that contention unfairness primarily occurs in MHWNs when the source node i observes a continuous busy channel due to the overlapping transmission by a set of independent links in MICS M_a ($I(i,a)$). The probability that all the links in $I(i,a)$ are idle reduces to the product of the individual p_{LI_j} for all $j \in I(j,a)$. Hence, the information about the average waiting time to successfully schedule one packet represents the contention experienced by the node. The time line is divided into equally spaced *epochs*. During each epoch, the contention metric ($C(X)$) and the current $\mathrm{CW}_{\min}$ of node X is piggybacked with the packet. Promiscuous mode is enabled at all the nodes in order to overhear neighbors' packet. An alternative approach would be to broadcast contention information. However, this approach incurs added broadcast overhead for the small size of the contention information. Moreover, the congested sources rarely capture the channel and contending for broadcast packet in an already congested channel is undesirable.

Upon receiving the contention information from the neighbors, each node updates the neighbors' contention information and, if necessary, adaptively alters its backoff window $\mathrm{CW}_{\min}$. Each node maintains a "Contention Information Table" where it stores the $\mathrm{CW}_{\min}$ and $C(X)$ of the neighbor. In order to support the network dynamism, each neighbor entry is purged if the contention information is not updated for a certain period of time. We now discuss the two main parts of the algorithm: $C(X)$ metric and the $\mathrm{CW}_{\min}$ update procedure.

Congestion information $C(X)$*:* Recall that the weak link faces severe starvation due to overlapping transmissions. The average wait time to transmit one packet $\overline{W_t}$ (synonymous to the expected value in Equation 10) and the number of channel gaps observed $\overline{G_n}$ are two primary quantities that highlights the degree of starvation. For example, the weak link B in the FIM example, experiences a very high $\overline{W_t}$ and $\overline{G_n}$. The advantages of using these metrics is that they can be directly measured at the node without any overhead of communication. While $\overline{W_t}$ is sufficient information to describe the starvation and mitigates contention, we have observed that the product $\overline{W_t}.\overline{G_n}$ leads to faster convergence and hence use this product as the congestion information $C(X)$.

$\mathrm{CW}_{\min}$ *update procedure:* The node uses an Additive Increase Additive Decrease (AIAD) approach to alter the $\mathrm{CW}_{\min}$. While other mechanisms like Multiplicative Increase Additive Decrease (MIAD) can be employed, the channel access probability is very sensitive to the changes in the $\mathrm{CW}_{\min}$ and severe short-term unfairness can be observed by drastic updates. In order to avoid the oscillation between frequent increments and decrements, the node observes the following rules.

(1) The nodes increment (or decrement) the $\mathrm{CW}_{\min}$ only if the contention information $C(X)$ of its most contended neighbor is greater (or lesser) than a factor of its $C(X)$.

(2) Each node maintains a *state* which signifies its current alteration procedure. The four states of the node are $\{Dec, Dec^+, Inc^-, Inc\}$. The node increments (or decrements) the backoff window only when it is in the pure increment "*Inc*" (or pure decrement, "*Dec*") state. Transition from *Inc* to *Dec* happens only through the transient states Inc^- and Dec^+.

(3) The $\mathrm{CW}_{\min}$ is incremented only if the neighbor's $\mathrm{CW}_{\min}$ is

lesser than the nodes $\mathrm{CW}_{\min}$. A higher $\mathrm{CW}_{\min}$ of the neighbor may also signify a neighbor who is waiting for other starved neighbors and not a starved neighbor. Similar approach is taken for decrementing $\mathrm{CW}_{\min}$.

5.2 Validation by simulations

In this section, we evaluate the effectiveness of the protocol by simulation. We use the QualNet simulator [16] with default parameters and alter the backoff procedure according to the CABS. We first analyze the FIM example and then evaluate the random scenarios.

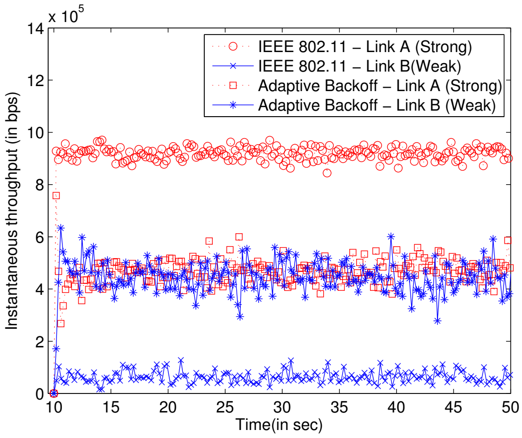


Figure 7: Instantaneous Throughputs: Long-term starvation for link B in IEEE 802.11. CABS shows a fast convergence to a fair throughput

FIM scenario. In the FIM scenario, the weak link B suffers severe unfairness under the default backoff mechanism due to constant busy channel from the stronger links A and C. Figure 7 compares the proposed CABS with the default backoff mechanism of IEEE 802.11 with a saturated CBR traffic packet with 200 bytes packets. Link B obtains only about 6% of link A/C's throughput under IEEE 802.11. The figure also demonstrates that the CABS attains superior long term fairness. However, regulating the short term fairness in FIM scenario is challenging since it is hard to ensure sufficient channel gaps to B (in the presence of the overlapping transmissions from A and C) in short intervals. TDMA based slotted access schemes can ensure such short term fairness. However, efficient slot assignment in a multi-hop wireless networks, with possibly varying packet sizes, incurs additional overhead and the objective of the CABS was to demonstrate fairness properties in a pure CSMA scheduling.

General scenarios. This section describes the results of random scenarios with varying number of one-hop connections. We compare the fairness of the connections using Jain's fairness index [12]. Jain's fairness index $f(x_1, x_2, \ldots, x_n)$ for n connections with throughputs $(x_1, x_2, \ldots, x_n)$ is defined as $\frac{(\sum_{i=1}^{n} x_i)^2}{n \sum_{i=1}^{n} x_i^2}$. This index maps the fairness of the flows to a number between 0 and 1, 0 being unfair and 1 being completely fair.

Table 1 summarizes the performance of the CABS by varying the number of one-hop flows in the network. We simulated 25 random scenarios with varying number of one-hop connections, each with 200 bytes packet size and CBR traffic. The ratio of the fairness index (and throughput) of CABS scheme and IEEE 802.11 protocol is shown in the Table 1. An average improvement of 25% is seen in the fairness levels. More than 50% of the scenarios even show an improvement of around 80%. The investigation into the individual scenarios reveal that a significant improvement in fairness can be achieved when: (1) A link is present only in the lower order MICS (MICS with lesser number of links). (2) Transition to certain MICS is only possible when multiple independent links are idle. The results also indicate that contention unfairness is *not a rarely occurring phenomenon* and can be mitigated by the proposed techniques that have very little overhead.

Metric \ Num Flows	4	5	6
Fairness Ratio	1.22	1.24	1.3
Throughput Ratio	0.9	0.86	0.83

Table 1: Performance study of CABS: Ratio of performance metric in CABS to IEEE 802.11

While the simulation demonstrates the feasibility of achieving fairness through simple protocols, the dissemination of the contention information is not reliably transmitted to all the interfering sources. Some interfering sources fail to capture the contention information packet due to low signal strength or due to overlapping transmissions from independent set neighbors. Disseminating this information in single channel and within the the small durations of channel gaps is challenging and is a part of our future work.

6. RELATED WORK

Modeling CSMA protocols in MWHNs is a classical problem (e.g., [5, 19]) and extensions to model IEEE 802.11 are proposed (e.g., [8, 22]). Wang *et al.* [22] propose a logical extension of Boorstyn's model [5] to account for 802.11. However, the model does not accurately account for subtle, yet significant, effects of the protocol such as DIFS. Moreover, since the methodology used in the above model does not explicitly consider transition between the maximal independent sets, it was not used to derive the important aspects of contention unfairness such as channel gaps and its distribution. We showed that such information provides valuable insights in predicting the effect of contention unfairness. Garetto *et al.* [8] propose an 802.11 model using an iterative approach that converge to the solution. While using such iterative schemes provide accurate solution, the mechanisms for updating the parameters during each iteration mask the understanding of the underlying phenomenon and the convergence to the solution is observed after a large number of iterations. In contrast, our work provides a low-complexity constructive approach that models the essential details, like channel gaps, in a more direct fashion. While Chaudet *et al.* [6] analyze the FIM example, the model is not generic to capture general contention unfairness.

Various distributed protocols achieve fairness among the contending nodes in MHWN by dynamic tuning of the backoff parameter [4, 3, 7]. A majority of the approaches consider altering the backoff window to provide fairness under a hidden-terminal scenario which does not directly solve the contention unfairness problem [4, 3, 1, 7]. Certain approaches recommend: (1) decreasing the backoff window after a successful transmission [1, 7, 4], (2) contending with lesser probability when channel is observed busy or when a packet collision occurs [15] (3) choosing similar backoff values [4] at all the neighboring nodes, or (4) setting a backoff value after observing a certain number of idle slots on the channel [11]. While such approaches achieve fairness by reducing packet col-

lisions and concurrent transmissions, with the simple example of "Flow in the Middle", it can be seen that they do not solve the contention unfairness problem. We showed that links A and C in Figure 1 should have a much higher $\mathrm{CW}_{\min}$ than B, which is not achieved by the above schemes. In fact, unfairness problem is exacerbated in schemes that:
(1) increase the probability of channel access to link A and C (by decreasing $\mathrm{CW}_{\min}$ or increasing the persistence probability) upon successful transmission [1, 7, 4]
(2) decrease the probability of channel access to link B upon observing a busy channel [15].

7. CONCLUSIONS AND FUTURE WORK

In this paper, we analyzed the fairness issues arising due to the inherent nature of CSMA contention in MHWNs. We have proposed an accurate throughput estimation model that accounts for contention fairness. In addition to adopting a constructive approach and deriving the primary parameters that affect contention unfairness, the model provides a general framework to handle varying packet sizes and backoff parameters. The insights gained from the model was used to propose a *contention-aware adaptive backoff scheme*. This backoff adaptation mechanism converged to provide fair access to starving links with an acceptable throughput degradation.

Our immediate future work is to extend the framework to account for routing effects such as pipelining, where the traffic from one hop feeds the next hop, in a computationally efficient model. The model can also be extended in designing optimal backoff parameters to avoid unfairness.

Another area of future work is the application of the model in various protocols and tools for optimizing the network performance in real-time. We are currently working on measurement-based protocols that measure the parameters like error rate and signal strength, and utilizes the model to dynamically detect the effect of interactions. Such protocols hold promise in realizing the insights from the model to a variety of applications such as provisioning, QoS and network monitoring tool.

Acknowledgements

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