Capacity-Aware Routing in Heterogeneous Mesh Networks: An Analytical Approach*

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ABSTRACT

In wireless mesh networks (WMNs), gateway nodes may become a severe bottleneck for Internet flows. Indeed, if traffic is routed in the mesh without considering traffic distribution, as well as link capacities, some gateways or intermediate mesh routers may rapidly get overloaded due to unevenly utilization of network resources. To address this issue, in this paper we firstly develop a multi-class queuing network model to analyze feasible throughput allocations in heterogeneous WMNs, as well as to predict the residual capacity of network paths. Guided by our analysis, we design a *Capacity-Aware Route Selection* algorithm (*CARS*), which allocates network paths to downstream and upstream Internet flows so as to ensure a more balanced utilization of wireless network resources and gateways' Internet connections. Through simulations in a number of different network scenarios we show that CARS significantly outperforms shortest path routing using routing metrics that capture only inter-flow interference.

Categories and Subject Descriptors

C.2.2 [**Computer-Communication Networks**]: Network Protocols—*Routing protocols*; C.4 [**Performance of Systems**]: Modeling techniques.

General Terms

Theory, Performance, Algorithms.

Keywords

Wireless mesh networks, queuing networks, routing, load balancing, performance evaluation.

*This work was supported in part by the European Commission in the 7FP through project EU-MESH, ICT-215320, and by the Italian National Project WORLD, under grant number 2007R989S.

1. INTRODUCTION

Wireless mesh networks (WMNs) are increasingly deployed to provide cost-effective ubiquitous access to the Internet [13]. Normally, in WMNs a set of stationary wireless mesh routers form a multi-hop wireless backbone, where a small subset of these routers act as *gateways* being connected to the Internet through high-speed fixed lines [6]. However, this vision is rapidly changing. Real-world mesh networks are frequently used to share a potentially large number of low-speed Internet connections (i.e., DSL fixed lines) available at the customers' premises [20]. In a broader sense, wireless mesh networks are evolving into a *converged infrastructure* used to share the Internet connectivity of sparsely deployed fixed lines with *heterogeneous capacity*, ranging from ISP-owned broadband links to subscriber-owned low-speed connections [21].

Being mesh networks primarily used for Internet access, both traffic routing and Internet gateway selection play a crucial role in determining the overall network performance, and in ensuring the optimal utilization of the mesh infrastructure [26]. Indeed, depending on the location of the mesh nodes and the gateways, some of the mesh nodes may obtain substantially lower throughput than others. Similarly, if many mesh nodes select the same gateway as egress (ingress) point to (from) the Internet, congestion may increase excessively on the wireless channel, or the Internet connection of the gateway can get overloaded. This problem is particularly relevant in the heterogeneous WMNs considered in this study, because low-speed Internet gateways may easily become a *bottleneck*, limiting the achievable capacity of the entire network. In addition, a load-unaware gateway selection can lead to an unbalanced utilization of network resources.

To improve load balancing and increase capacity of WMNs, previous studies suggested to use balanced tree structures rooted at the gateways, and to route the traffic along the tree paths [3,18]. However, tree-based routing structures are less reliable to link failures than mesh-based structures. Furthermore, the admission of a new flow usually triggers complex reconfiguration procedures for the entire tree. A simpler approach to improve network performance is to define routing metrics for shortest-path first (*SPF*) routing that determine high-throughput paths and/or facilitate load balancing. Initially proposed metrics (e.g., ETX [9] and ETT [10]), focused only on link characteristics, while recent studies have proposed to also consider inter-flow and intra-flow interference (e.g., IRU [25]), location-dependent contention (e.g., CATT [12], ETP [18]) or load-dependent cost (such as the queue length in WCETT-LB [16], or the number of per-link admitted flows in LAETT [1]). Although these metrics have been demonstrated to work quite well in mesh networks, and to provide higher throughput performance than simple hop count, they are completely unaware of the available resources at the gateways. On the contrary, significant performance improvements might be obtained by considering residual capacity of gateways' Internet connections, as well as load distributions, when routing traffic flows. However, there is a complex interdependence between the way traffic flows are routed in the network and the utilization of network resources, which makes quite difficult to define simple heuristics to estimate the remaining capacity of a network path or a gateway.

To address the above problems, in this paper we make the following contributions. We develop a *multi-class queuing network model* for heterogeneous WMNs, which is used to determine if a given allocation of flows on a set of network paths is feasible. Our model takes into account the per-flow bandwidth demands, the distribution of gateways in the WMN, the heterogeneity of link capacities, as well as the location-dependent contention on the wireless channel. Then, given the routing strategy used to allocate the flow demands on the network paths, we exploit our model to establish if the resulting flow allocation does not violate the network capacity constraints. In addition, the analysis also provides an estimation of the residual capacity of links and network paths. To validate our modeling methodology, in this study we consider a basic CSMA-based MAC protocol, which implements an idealized collision avoidance mechanism that can always detect if the medium is busy or free before a transmission attempt. Although in a simplified form, the considered MAC scheme captures the location-dependent contention inherent to multi-hop environments, and due to differences in the number of contending nodes at both endpoints of each communication link.

It is important to point out that several previous studies have proposed to use queuing models to investigate system performance of CSMA-based ad hoc networks. However most of these studies have applied queuing theory to the analysis of *single-hop* ad hoc networks [2, 19, 22]. To the best of our knowledge, in literature a few examples exist which deal with the multi-hop case. In [4], the authors model random access multi-hop wireless networks as open $GI/G/1$ queuing networks to analyze the average end-to-end delay and maximum achievable per-node throughput. However, the formulation proposed in [4] can be applied only to random networks, and it does not incorporate flow-level behaviors. Our objective is different from [4], because we consider arbitrary topologies and routing strategies, and we focus on per-flow performance. In our previous paper [7] we have developed a single-class queuing model to analyze the network capacity of heterogeneous WMNs. However, the analysis in [7] is valid only for upstream Internet traffic, which is a somehow unrealistic traffic model for typical WMNs. On the contrary, in this paper we extend our previous analysis to incorporate generic traffic distributions, which motivates the use of a novel modeling methodology based on multi-class queuing networks.

Guided by our analysis, in this paper we propose a *Capacity-Aware Route Selection* algorithm (*CARS*), which integrates traffic routing with gateway selection. Instead of using shortest-path first (*SPF*) routing, CARS scheme determines the set of optimal routes from the mesh node that originates the new flow, and the available gateways. Then, CARS allocates the new flow to the best network path that has enough residual capacity (as predicted by our model) to satisfy its bandwidth demands. In this way, a mesh node can discard paths or gateways that cannot accept additional demands. This facilitates load balancing in the network by avoiding the rapid exhaustion of link capacities of disadvantaged mesh nodes or gateways, leading to a more efficient utilization of both wireless and wired network resources. Through simulations performed in network scenarios with different numbers of gateways and link capacities, we show that CARS scheme results in significant throughput improvements over shortest-path first routing using IRU metric [25], which captures only inter-flow interference (i.e., mutual interference between adjacent flows). Furthermore, the simulation results confirm the accuracy of the proposed modeling methodology.

The remaining of this paper is organized as follows. Section 2 introduces the network model. In Section 3 we develop the capacity analysis. Section 4 describes the proposed CARS algorithm. In Section 5 we present simulation results to validate the analysis, and to compare CARS performance with shortest path routing using IRU metric. Finally, conclusions and future work are discussed in Section 6.

2. NETWORK MODEL

In this work we are concerned with *heterogeneous* wireless mesh networks (WMNs), which consist of fixed wireless routers, also called *nodes*, and mobile or semi-static end-user stations, also called *clients*. Each mesh node is equipped with a dedicated access point to aggregate the traffic originated by mesh clients within its coverage area. Thus, mesh nodes constitute a wireless mesh backbone providing a wireless infrastructure for mesh clients. Some of the mesh nodes have also a physical link to a wired network (i.e., Internet), and they serve as *gateways* between the WMN and this external network. All the resources residing on the wired network (e.g., files or application servers) can be accessed through any of the available gateways.

Differently from previous studies, which generally assume a limited number of mesh gateways connected to the external wired network with an unlimited-bandwidth fixed link, in this work we consider different classes of mesh gateways. More precisely, we consider mesh gateways connected to the wired network using low-speed links, as well as mesh gateways connected to the wired network using very high-speed links. As discussed in Section 1, the former category of gateways can model mesh routers located at the end-user side, which are generally connected to the Internet through residential access lines (e.g., DSL or cable lines), whereas the latter category can model mesh routers located at the provider's premises, which have a high-speed connection to the Internet (e.g., fiber or point-to-point high-capacity wireless links). Hereafter, we will refer to the first type of gateways as *residential gateways*, and to the second one as *provider gateways*.

A second relevant difference between the network model targeted in this work and the architecture of WMNs generally adopted in previous studies is that we relax the assumption on symmetric capacity for fixed access lines. More precisely, the distinguishing characteristic of DSL-based technologies is that the upload speed is generally lower than the download speed. This asymmetry in the bandwidth for the two transmission directions may have a significant impact on the overall network capacity if not properly taken into account during the routing process. To the best of our knowledge, previous studies have only considered the case of wired communications technologies with symmetric bandwidth for both directions.

To represent the above network model, let us introduce $\mathcal{G}_r$ as the set of residential gateways, $\mathcal{G}_p$ as the set of provider gateways, and $\mathcal{M}$ as the set of mesh routers without a physical connection to the wired network. Let n_w, n_r and n_p be the cardinality of $\mathcal{M}$, $\mathcal{G}_r$, and $\mathcal{G}_p$ sets, respectively, with $n = n_w + n_r + n_p$. Then, the network is modeled using a mixed graph $G(V \cup \{a\}, E_w, E_g)$, where the graph vertexes, V ($|V| = n$), represent the mesh nodes (i.e., $V = \mathcal{G}_r \cup \mathcal{G}_p \cup \mathcal{M}$) and a is a virtual node that corresponds to the fixed infrastructure. We denote by E_w the set of undirected edges representing the wireless links between mesh nodes, while E_g is the set of directed edges representing the network links between the gateways and the infrastructure. The neighborhood of node $v \in V$, denoted by $N(v)$, is the set of nodes to which node v is physically connected. If node v is a gateway, the virtual node a is included in the neighborhood of v.

Each link $e \in E_w$ has a capacity (bit rate) C_w for both directions, whereas each link $e \in E_g$ has a capacity that depends on the direction of the communication, as well as on the gateway class. More precisely, we assume that a link $e \in E_g$ from a residential gateway $i \in \mathcal{G}_r$ to the wired infrastructure a has capacity C_r^u, and from a to gateway i has capacity C_r^d, respectively. Analogously, we assume that a link $e \in E_g$ from a provider gateway $i \in \mathcal{G}_p$ to the wired infrastructure a has capacity C_p^u, and from a to gateway i has capacity C_p^d, respectively. It is important to note that in this work we are primarily concerned with *Internet traffic*. In other words, we assume that user traffic is either originated from or is destined for the fixed infrastructure, so that the traffic flows always traverse the gateways, while non-gateway nodes serve as relays.

Concerning the physical layer model of the wireless communication channel, we assume that the *transmission range* of each station is fixed and equal to r. Moreover, a pair of mesh nodes that are within their *interference range* may interfere with each other's transmissions, even if they cannot directly communicate. To model the interference relationships between contending mesh nodes we use the Protocol Model as in [4,7]. In other words, a transmission from mesh node u to mesh node v, with $u, v \in V$, is successful if the following conditions are satisfied: 1) $|u-v| \leq r$ and 2) for every other transmitting node k, $|k-v| \geq (1+\Delta)\cdot r$, where Δ is a fixed positive constant that represents a guard zone in the Protocol Model.

To coordinate simultaneous transmissions of interfering nodes we employ a basic CSMA-based MAC protocol, which implements an idealized collision avoidance mechanism. More precisely, we assume that each node has an instantaneous knowledge of the communication state (i.e., idle, receiving or transmitting) of other interfering nodes, so as to ensure that it starts transmitting only when both above conditions can be satisfied. This is somehow equivalent to determine a collision-free random transmission schedule among contending nodes. This assumption might be considered restrictive, especially because we neglect the detailed protocol implementation of collision avoidance and resolution mechanisms, such as 802.11-like backoff schemes. However, though in a simplified form, the considered MAC scheme captures the fundamental aspects of location-dependent contention inherent to multi-hop environments, which is due to differences in the number of contending nodes at both endpoints of each communication link. In other words, in this study we are more concerned on modeling the link capacity degradation due to location-dependent contention, rather than precisely incorporating in the analysis all the features of the IEEE 802.11 MAC protocol.

3. CAPACITY ANALYSIS

In this section we develop a queuing-based analysis to determine the network capacity of the WMN architecture described above.

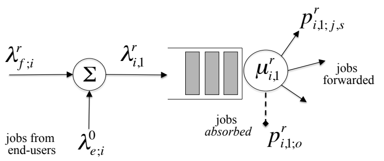
3.1 Multi-Class Queuing Network

The first step of our analysis is to define a representation of an heterogeneous WMN, i.e. $G(V \cup \{a\}, E_w, E_g)$, through an equivalent *multi-class* queuing network $G'(Q, L)$, where Q is the set of queuing systems in the network, for brevity *stations*, which model the real mesh nodes, and L is the set of connections between stations. First of all, it is important to discuss the reasoning behind using a multi-class queuing network. Intuitively, jobs in the queuing network represent packets in the physical network[1]. However, each packet may have a different destination (either a mesh node or the wired infrastructure), and may belong to traffic flows with different bandwidth demands. Hence, multiple job classes might be a flexible technique to model different traffic flows. More precisely, packets of a flow originated in the wired infrastructure, which enters the WMN from gateway i ($i \in \mathcal{G}_r \cup \mathcal{G}_p$), and have mesh node r ($r \in V$) as intended destination, are modeled as jobs of class r. For simplicity, we characterize this traffic flow through its average packet arrival rate, say $\lambda^r_{a;i}$. On the other hand, packets of a flow originated from mesh node i ($i \in V$), and heading to the wired infrastructure (i.e., virtual node a), are modeled as jobs of class 0. For simplicity, we characterize this traffic flow through its average packet arrival rate, say $\lambda^0_{e;i}$. Being n the number of mesh nodes, the number of classes needed to model all the possible traffic flow destinations is $R = n+1$. It is also worth pointing out that job classes can differ in their service times and in their routing probabilities, which ensures a high modeling flexibility.

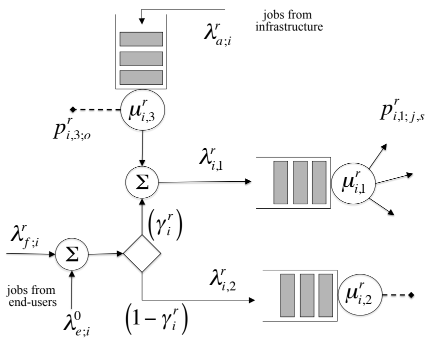
Basing on our analogy between the physical network and an equivalent queuing network, each mesh node $i \in V$ is modeled through a service station $j \in Q$. In general, this equivalent queuing station may include several queues to capture the most important features of the multiple network interfaces (for both wired and wireless technologies), which a mesh node is equipped with. For brevity, let $q(j)$ be the number of queues in station j. It is intuitive to note that, being the WMN composed of two classes of nodes, gateway and non-gateway nodes, at least two different queuing station models should be specified for the analysis. For ease of explanation, Figure 1 exemplifies the structure of the queuing stations used to model mesh nodes.

Figure 1(a) illustrates a station modeling a wireless mesh router i ($i \in \mathcal{M}$) not connected to the wired infrastructure.

[1] In the following, the terms job and packet are used equivalently.



(a) Non-gateway mesh node



(b) Gateway mesh node

Figure 1: Equivalent queuing stations used to model mesh nodes.

This station consists of a singe queue (i.e., $q(i) = 1$), say $q_{i,1}$, which models the transmissions on the wireless channel. Let us denote with $\mu^r_{i,1}$ the average service rate for jobs of class r at queue $q_{i,1}$. Regarding the job arrival process, we can observe that mesh node i aggregates the traffic flows originated from the mesh clients associated with it. Then, we model this aggregated traffic through its average packet arrival rate $\lambda^r_{e;i}$. Since we do not consider communications between mesh clients but only between mesh clients and the Internet, it holds that $\lambda^r_{e;i} = 0$ for $r \neq 0$. In addition to locally generated jobs, station i receives jobs forwarded by neighboring mesh nodes, with average arrival rate $\lambda^r_{f;i}$. Hence, the total arrival rate at queue $q_{i,1}$ is $\lambda^r_{i,1} = \lambda^r_{f;i} + \lambda^r_{e;i}$. Finally, after being served from queue $q_{i,1}$, a job of class r will be transferred to the s-th queue of the j-th station with probability $p^r_{i,1;j,s}$. In other words, $p^r_{i,1;j,s}$ is the *routing probability* that models the packet forwarding process implemented in the physical network. If the next station is the intended destination of the packet at the head of queue $q_{i,1}$ (i.e., $r = j$), then the class r job is *absorbed* by node i just after completing the service at queue $q_{i,1}$, thus leaving the network. We denote with $p^r_{i,1;o}$ this absorption probability.

Figure 1(b) illustrates a station modeling a gateway node i ($i \in \mathcal{G}_r \cup \mathcal{G}_p$). In this case, the internal structure of the queuing station is more complicated because we need three queues $q_{i,1}$, $q_{i,2}$ and $q_{i,3}$ (i.e., $q(i) = 3$), to model wireless transmissions, uplink wired transmissions and downlink wired transmissions, respectively. Specifically, each gateway i may receive packets from the wired infrastructure having mesh node r as intended destination. These packets will be routed through queue $q_{i,3}$, and we denote with $\lambda^r_{a;i,3}$ their average arrival rate. Note that if $r = i$, then the mesh clients associated to this gateway are the packet destination, and the jobs are absorbed after being served at queue $q_{i,3}$. On the other hand, gateway i may receive packets forwarded by neighboring mesh nodes, with average arrival rate $\lambda^r_{f;i}$, as well as packets generated by associated mesh clients, with average arrival rate $\lambda^r_{e;i}$. If $r = 0$, the packet destination is the wired infrastructure (i.e., the virtual node a) and the packet should be routed through queue $q_{i,2}$, which models the wired access line in the uplink direction. However, a residential gateway may have a low-speed upstream connection to the Internet, which rapidly becomes a bottleneck as the traffic received on the wireless interface builds up, limiting the achievable capacity of the whole mesh network. To make this limitation less severe, the residential gateway may take advantage of the available wireless bandwidth to behave as a relay node, and further forwarding the traffic to one of its neighbors, which may be less congested, or closer to a provider gateway. To model this capability we introduce the *re-forwarding* probability γ^r_i. Specifically, a job of class r received by gateway i is routed through the wireless queue $q_{i,1}$ with probability γ^r_i, or directly through the upstream wired queue $q_{i,2}$ with probability $(1 - \gamma^r_i)$. The design of the γ^r_i function depends on the routing and resource allocation strategies implemented in the mesh network. Note that in our model $\gamma^r_i = 1$ for $r \neq 0$ because communications between mesh gateways through the wired infrastructure are not permitted. In other words queue $q_{i,2}$ can be used only by upstream flows to access the Internet (i.e., virtual node a).

For simplicity, in this study we assume that all queues have infinite size and serve packets according to a FCFS discipline.

3.2 Network Capacity

In this section we develop the analysis to determine if a given throughput allocation in $G(V \cup \{a\}, E_w, E_g)$ is *feasible*. Before formally defining when a throughput allocation is feasible, and describing our analytical methodology, it is useful to introduce some notation.

Let us denote with λ_o the overall arrival rate of jobs from *outside* to the mesh network. Furthermore, let $p^r_{o;i,l}$ be the probability that a job from outside the network enters the l-th queue of the i-th station as a job of the r-th class. This yields that the arrival rate from outside to queue l of station i (i.e., $q_{i,l}$) for class r jobs is $\lambda^r_{o;i,l} = \lambda_o \cdot p^r_{o;i,l}$. For the sake of brevity, we introduce the *probability matrix of external arrivals* defined as $\mathbf{P_o} = \{p^r_{o;i,l}, i \in Q, l \in [1, q(i)], r \in [1, R]\}$. Note that this notation conforms to the network model formulated in Section 3.1. For instance, for gateway i it holds that $\lambda^r_{o;i,3} = \lambda_o \cdot p^r_{o;i,3} = \lambda^r_{a;i,3}$. Thus, from a given value of λ_o it immediately follows that $p^r_{o;i,3} = \lambda_o / \lambda^r_{a;i,3}$. Similar reasoning can be applied to derive the probability $p^r_{o;i,l}$ for the internal queues of each mesh node.

Definition 1. **Throughput allocation.** *A throughput allocation for $G(V \cup \{a\}, E_w, E_g)$ is any assignment for the rate λ_o and the probability matrix $\mathbf{P_o}$.*

In Section 3.1 we have introduced the routing probability $p^r_{i,l;j,s}$ defined as the probability that a job of class r is transferred from the queue l of station i (i.e., $q_{i,l}$) to queue s of station j (i.e., $q_{j,s}$). Following the equivalency between the real WMN and the queuing network, the $p^r_{i,l;j,s}$ value expresses the probability that mesh node i selects mesh node j as next-hop to reach destination r. The queue indexes are used to specify if the packet is transmitted using the wireless links or the wired fixed lines. For the sake of brevity, we introduce the network *routing matrix* defined as

$\mathbf{R_{fwd}} = \{p^r_{i,l;j,s}, i,j \in Q, l \in [1,q(i)], s \in [1,q(j)], r \in [1,R]\}$, which is the probabilistic representation of the underlying routing process. It is intuitive to observe that the specific formulation of the routing matrix depends on the routing algorithm used in the WMN, as well as the network topology.

The following definition specifies when a throughput allocation is feasible.

DEFINITION 2. **Feasible throughput allocation.** *Given a routing matrix $\mathbf{R_{fwd}}$, a throughput allocation is feasible if every queue $q_{i,l}$ ($i \in Q$ and $l \in [1,q(i)]$) has a bounded time-average number of packets. This is equivalent to state that arrival process at queue $q_{i,l}$ is admissible with rate $\lambda^r_{o;i,l}$.*

Definition 2 implies that a throughput allocation is feasible if all the queues in the system are stable, i.e., the number of jobs waiting in queue does not grow indefinitely.

To verify the queue stability we have to compute the queue's *utilization factor* [5]. From elementary queuing theory this requires the evaluation of the first moments of the packet arrival and service processes at each queue of the network. Specifically, under the assumption that service rates are independent of the queue load, the utilization $\rho^r_{i,l}$ of the queue l at node i (i.e., $q_{i,l}$) with respect to jobs of the r-th class is

$$\rho^r_{i,l} = \frac{\lambda^r_{i,l}}{\mu^r_{i,l}} \ , \tag{1}$$

where $\lambda^r_{i,l}$ is the average packet arrival rate of class r jobs at queue $q_{i,l}$, and $\mu^r_{i,l}$ is the corresponding average service rate. Then, the overall utilization of queue $q_{i,l}$ can be computed as:

$$\rho_{i,l} = \sum_{r=0}^{R} \rho^r_{i,l} \ . \tag{2}$$

By definition, an infinite-size queue is stable if and only if $\rho_{i,l} < 1$.

The average rate $\lambda^r_{i,l}$ can be computed from λ_o, $\mathbf{P_o}$ and $\mathbf{R_{fwd}}$ by solving the following system of linear equations:

$$\lambda^r_{i,l} = \lambda_o \cdot p^r_{o;i,l} + \sum_{j=1}^{n} \sum_{s=1}^{q(j)} \lambda^r_{j,s} p^r_{j,s;i,l} \ \text{for } i \in Q, l \in [1,q(i)] \ , \tag{3}$$

obtained by writing the flow balance condition at each queue of the system.

The average service rates for the queues modeling transmissions on either uplink or downlink wired links can be easily derived by observing that in switched communication technologies there is no contention. Hence, average service times depend only on the nominal link capacity and the packet size. Then, under the assumption that the packet size is constant and equal to P bits, it holds that

$$\mu^r_{i,l} = \begin{cases} P/C^u_r & i \in \mathcal{G}_r, l = 2 \\ P/C^d_r & i \in \mathcal{G}_r, l = 3 \\ P/C^u_p & i \in \mathcal{G}_p, l = 2 \\ P/C^d_p & i \in \mathcal{G}_p, l = 3 \end{cases} \ . \tag{4}$$

On the other hand, the derivation of the average service rate for the queues modeling transmissions on the wireless channel is more involved because it is necessary to take into account the location-dependent contention, the distributions of active queues (i.e., queues with at least a packet to serve) and the channel access coordination procedures implemented by the MAC protocol. Several stochastic models have been developed to analyze the access delays of CSMA-based MAC protocols used in multi-hop environments. Recall from Section 2 that in this work we consider a basic collision-free CSMA-based MAC protocol, and we assume that each mesh node has an instantaneous knowledge of the communication state of other interfering nodes. Then, following the footprints of [11] and our previous work [7], we can model the impact on the channel access of location-dependent contention by employing an *average value analysis*, and considering only the long-term fraction of time each mesh node spends in one of three potential states: transmission state, receiving state, and idle state. This modeling approach will lead to a mathematically manageable, but still reasonable accurate, analysis.

To compute the $\mu^r_{i,1}$ parameter[2] we analyze the channel events during the $X^r_{i,1}$ period, defined as the interval from the time instant a class r job reaches the head of queue $q_{i,1}$ to the time instant in which it is transferred to the next-hop station. Then, it holds that $\mu^r_{i,1} = 1/E[X^r_{i,1}]$, where $E[\cdot]$ is the expectation operator. To simplify the derivation of the $E[X^r_{i,1}]$ expression we condition to the possible destinations of a class r job served at queue $q_{i,1}$. Specifically, owing to the conditional expectation theory we can write that

$$E[X^r_{i,1}] = \sum_{j=1}^{n} \sum_{s=1}^{\min\{2,q(j)\}} E[X^r_{i,1;j,s}] \cdot p^r_{i,1;j,s} \ , \tag{5}$$

where $X^r_{i,1;j,s}$ is the time needed to transfer a job of class r from queue $q_{i,1}$ to queue $q_{j,1}$. This time will mainly depend on the level of contention around the transmitting station i and the receiving station j, i.e., on the distribution of interfering nodes in the network, as well as on their activity level, i.e., the fraction of time these nodes contend for the channel access.

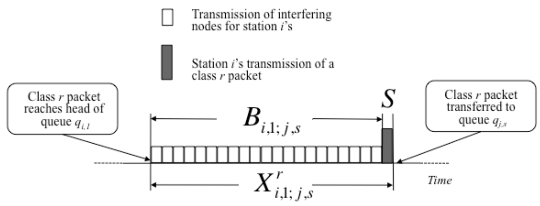


Figure 2: Illustrative example of the channel events during the transmission of a class r packet from $q_{i,1}$ to queue $q_{j,s}$.

For ease of explanation Figure 2 shows the evolution of channel events during a generic $X^r_{i,1;j,s}$ interval. As illustrated in the diagram, due to the random access scheme the transmission of a packet from queue $q_{i,1}$ to queue $q_{j,1}$ may be preceded by a number $z_{i,1;j,s}$ of transmissions by other contenting stations, which does not depend on the packet class[3]. Let us denote with $E[B_{i,1;j,s}]$ the average period of channel time occupied by other stations' packet transmissions, which precedes the service of the packet at the head

[2]Recall that $q_{i,1}$ refers to the queue at station i that models transmissions on the wireless channel.

[3]In the consider idealized CSMA-based MAC protocol transmission attempts are not preceded by backoff delays.

of queue $q_{i,1}$, given that this packet is heading to queue $q_{j,s}$. Then, under the assumption of fixed packet size, it is straightforward to derive that

$$E[B_{i,1;j,s}] = P \cdot E[z_{i,1;j,s}]/C_w. \quad (6)$$

This yields to the following expression for the $E[X^r_{i,1;j,s}]$ parameter.

$$E[X^r_{i,1;j,s}] = P \cdot (1 + E[z_{i,1;j,s}])/C_w\ . \quad (7)$$

An interesting result of expression (7) is that the $E[X^r_{i,1;j,s}]$ value does not depend on class r. This can be explained by noting that the impact of class r on the service time is taken into account in formula (5) through the per-class routing probabilities. However, it is also intuitive to note that the time needed to transfer a packet on a link from $q_{i,1}$ to $q_{j,s}$ using a random access scheme should not depend on the packet class but only on the contention level around station i and station j.

To derive a closed expression for the $E[z_{i,1;j,s}]$ parameter, the key approximation of our analysis is to assume that station i attempts to transmit a packet to station j immediately after the channel becomes idle again with a constant (state independent) probability equal to $\tau_{i,1;j,s}$. This approximation is commonly adopted when modeling CSMA-based random access schemes, and it also known as *decoupling* approximation [15]. While in single-hop networks it is generally assumed that all nodes have the same *transmission probability*, in our study the location-dependent contention is modeled by admitting different values of the $\tau_{i,1;j,s}$ probabilities. The decoupling approximation yields that $z_{i,1;j,s}$ is geometrically distributed with parameter $\tau_{i,1;j,s}$, that is

$$Pr\{z_{i,1;j,s} = h\} = (1 - \tau_{i,1;j,s})^h \tau_{i,1;j,s}\ . \quad (8)$$

Now, it is straightforward to derive that

$$E[B_{i,1;j,s}] = \frac{(1 - \tau_{i,1;j,s})}{\tau_{i,1;j,s}} \cdot S\ , \quad (9)$$

and formula (7) can be rewritten as $E[X^r_{i,1;j,s}] = P/(C_w \cdot \tau_{i,1;j,s})$.

The following lemma provides an explicit expression for the transmission probability $\tau_{i,1;j,s}$.

LEMMA 1. *Under the assumption that reception and transmission events in $G'(Q, L)$ are mutually independent, it holds that*

$$\tau_{i,1;j,s} = \prod_{h \in \mathcal{E}_i} \prod_{u=1}^{\min\{2,q(h)\}} (1 - \phi_{h,u} \cdot \omega_{h;j}) \cdot \prod_{k \in \mathcal{E}_j \cup \{j\}} (1 - \psi_{k,1})\ , \quad (10)$$

where

- $\phi_{h,u}$ *is the long-term fraction of time spent by queue* $q_{h,u}$ *receiving packets;*
- $\psi_{k,1}$ *is the long-term fraction of time spent by queue* $q_{k,1}$ *transmitting packets;*
- $\omega_{h,u;j}$ *is the fraction of wireless queues that are neighbors of station h, but they are not interferers for station j, and which have a not-null routing probability towards queue* $q_{h,u}$*;*
- $\mathcal{E}_i$ *is the set of mesh nodes in the interference region of node i (formally,* $\mathcal{E}_i = \{h : |h - i| \leq (1+\Delta) \cdot r\ ,\ h \in G)$*.*

PROOF. Due to space limitations we report the complete proof in our technical report [8] □

In summary, the analytical methodology we adopt to determine the feasibility of a throughput allocation consists of the following steps. First of all, from the WMN topology $G(V \cup \{a\}, E_w, E_g)$ we extract the equivalent queuing network $G'(Q, L)$. Then, given the throughput allocation (λ_o and $\mathbf{P_o}$), and the routing matrix $\mathbf{R_{fwd}}$, we can determine the overall arrival rate at each queue solving the linear system defined in (3). From the $\lambda_{i,l}$ values we compute the $\phi_{i,l}$ and $\psi_{i,1}$ parameters, and the $\tau_{i,1;j,s}$ probabilities using Lemma 1. This allows us to derive the average service times of each queue in the network, and to check the feasibility of the throughput allocation.

4. CAPACITY-AWARE ROUTE SELECTION

The most important outcome of the modeling methodology described in Section 3, is the development of a *predictive tool* that allow us to determine if a given routing matrix leads to an unfeasible throughput allocation. In this section we address a somehow opposite problem: given a set of flow demands, how to construct the routing matrix that makes the resulting throughput allocation feasible? Our goal is to design a fast and efficient strategy to discover feasible paths in an heterogeneous WMN. As a matter of fact, it is unrealistic to perform an exhaustive search because there are exponentially many paths between a source/destination pair, and a brute force strategy does not scale. For these reasons, in the literature various solutions have been proposed for reducing the complexity of this problem. A popular approach is to consider only disjoint and braided paths [23], but it is still computationally intensive to construct multiple disjoint paths. An alternative strategy is proposed in [18], where the complexity of finding optimal routes is mitigated by considering only routing forests, i.e., unions of disjoint trees rooted at the gateway nodes. However, tree-based structures are less reliable to link failures than mesh-based structures. The authors in [14] propose to transform the original network graph into an edge graph, where multiple links are aggregated into segments. This approach results into a reduction in the number of possible paths to check for feasibility, depending on the adopted segment size.

In this work we adopt a simpler approach by constructing a *routing mesh* from each mesh node to the available gateways. More precisely, for each mesh node i we compute the minimum cost paths towards each gateway j (with $j \in \mathcal{G}_r \cup \mathcal{G}_p$). Note that minimum cost path can be efficiently computed in a loop-free manner using Dijkstra and Bellman-Ford algorithms if the routing metric is *isotonic* [24]. Thus, the number of paths to check for feasibility grows linearly with the number of gateways and mesh nodes. The penalty we pay for this simplicity is that occasionally the routing process may not find a feasible route although it exists.

To explain the operations of the proposed *Capacity-Aware Route Selection* (*CARS*) algorithm, we adopt the following traffic model for the Internet flows. Specifically, in this study we assume that a bidirectional flow is established between the mesh node $v \in V$ and the wired infrastructure (represented by the virtual node a). This flow needs a certain bit rate to satisfy its QoS requirements. In general, the packet arrival rate can follow a generic distribution thus we express the bandwidth demands in terms of the average packet arrival rate. Now, let us assume that at time t the CARS algorithm has already admitted a set $\mathcal{F}^{(k)}$ of k Internet flows, $f^{(1)}, f^{(2)}, \ldots, f^{(k)}$, and that the i-th flow requested an uplink bandwidth and downlink bandwidth equal to $b_u^{(i)}$ and $b_d^{(i)}$, respectively. The *asymmetry* of flow demands is represented through the ratio $\eta^{(i)} = b_u^{(i)}/b_d^{(i)}$. For instance, If $\eta^{(i)} = 1$ then Internet flow $f^{(i)}$ is symmetric, $\eta^{(i)} = 0$ indicates a downlink Internet flow, while an uplink Internet flow is obtained when $\eta^{(i)} \rightarrow \infty$. Finally, let $\mathcal{P}^{(k)}$ be the set of k network paths chosen by the CARS algorithm to route these k flows so as to ensure a feasible throughput allocation in the network. From $\mathcal{F}^{(k)}$ and $\mathcal{P}^{(k)}$ it is straightforward to derive the throughout allocation $\lambda_o^{(k)}$ (e.g., $\lambda_o^{(k)} = \sum_{i=1}^{k}(b_u^{(k)} + b_d^{(k)})$), $\mathbf{P_o^k}$ and the routing matrix $\mathbf{R_{fwd}^{(k)}}$.

Now, let as assume that at time $t+1$ arrives a new flow $f^{(k+1)}$ originated at mesh node $v \in V$ with uplink and downlink bandwidth demands equal to $b_u^{(k+1)}$ and $b_d^{(k+1)}$, respectively. Then, CARS performs the following steps searching for a new routing matrix that permits to admit this new flow:

1. Update the throughout allocation by adding the new flow. Thus, the modified throughput allocation is $\lambda_o^* = \lambda_o^{(k)} + b_u^{(k+1)} + b_d^{(k+1)}$ and $\mathbf{P_o^*}$.
2. Construct two *optimal routing meshes* $\mathcal{Q}_u^{(k+1)}$ and $\mathcal{Q}_d^{(k+1)}$. The first one consists of the minimum cost paths from mesh node v to the available gateways, whereas the second one consists of the minimum cost paths from the available gateways to mesh node v. The paths in these sets are ordered from the one with the minimum path cost to the one with the largest one. Note that these path sets may be different depending on the formulation of the routing metric function. Moreover, heterogeneity of fixed line capacities may also lead to a different route selection for upstream and downstream flows.
3. Extract the minimum cost path in set $\mathcal{Q}_u^{(k+1)}$ and set $\mathcal{Q}_d^{(k+1)}$, say P_u^i and P_d^i, respectively.
4. Update the routing matrix by adding P_u^i and P_d^i to $\mathbf{R_{fwd}^{(k)}}$. Let denote with $\mathbf{R_{fwd}^*}$ the modified routing matrix.
5. *Check the feasibility* of throughput allocation $\lambda_o^{(*)}$ and $\mathbf{P_o^*}$ given the routing matrix $\mathbf{R_{fwd}^*}$. If the feasibility check is *positive* then **goto 7**, else **goto 6**.
6. Remove P_u^i and P_d^i from $\mathcal{Q}_u^{(k+1)}$ and $\mathcal{Q}_d^{(k+1)}$, respectively. If either one or both these sets are empty than *reject flow* $f^{(k+1)}$ and *exit(failure)*, else **goto 3**.
7. *Accept flow* $f^{(k+1)}$, and set $\lambda_o^{(k+1)} = \lambda_o^*$, $\mathbf{P_o^{(k+1)}} = \mathbf{P_o^*}$, and $\mathbf{R_{fwd}^{(k+1)}} = \mathbf{R_{fwd}^*}$. Then, *exit(success)*.

Before evaluating the performance of CARS scheme and investigating its load-balancing properties, it is useful to briefly discuss possible refinements of the CARS specification. First of all, we can observe that our model, in addition to check feasibility of throughput allocation, is able to identify which are the queues that get overloaded for a given throughput allocation. A possible enhancement for CARS would be to eliminate from the network topology the mesh routers or gateway nodes that are overloaded, and to re-compute the routing mesh sets for the modified topology. This would permit to consider longer paths able to route around congested network regions. Furthermore, in the CARS design the modified routing matrix $\mathbf{R_{fwd}^*}$, which is checked for feasibility, is computed starting from the previous routing matrix $\mathbf{R_{fwd}^{(k)}}$ without affecting the paths used by previously admitted flows. A possible alternative would be to adopt an approach similar to the one proposed in [18], and to accept partial reconfigurations of the selected network paths. However, the penalty for an improved adaptability of the routing process would be the increase of computational complexity, and a longer transient phase for network adaptation.

5. PERFORMANCE EVALUATION

In this section we use computer-based simulations to validate our analysis, and to compare the throughput performance gains of CARS scheme over a shortest-path first routing algorithm using IRU metric. For brevity, in the following we refer to this second scheme as *SPF-IRU*.

5.1 Simulation set-up

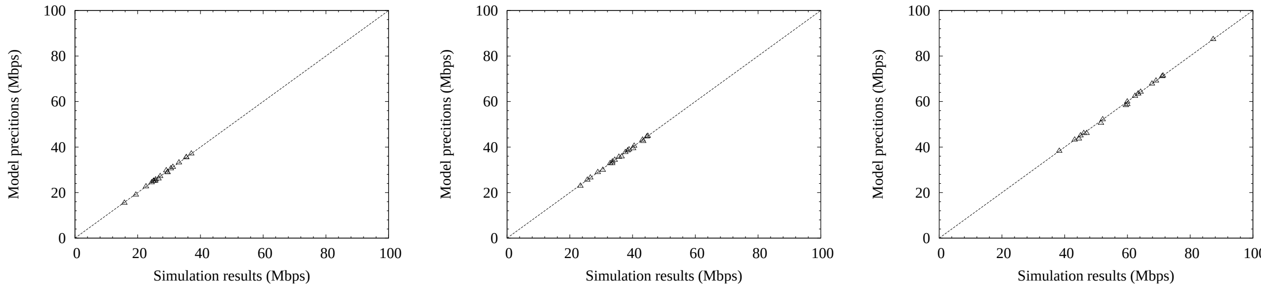
We have extended the discrete-event simulator used in our previous work [7] to support bidirectional Internet flows and arbitrary traffic distributions. In the following experiments, the nodes are deployed in a square area of size 1 Km. In the center of the simulated area we place a single provider gateway (i.e., $n_p = 1$), which has a high-speed Internet connection with $C_p^u = C_p^d = 1$ Gbps. Then, other 100 nodes (mesh routers and residential gateways) are deployed on a grid layout, with grid points separated by 100m. More precisely, we randomly pick up n_w grid points where we place mesh routers, and in the remaining n_r grid points we place residential gateways ($n = n_w + n_r = 100$). This ensures a sufficient degree of randomness in the locations of gateways. Moreover, we assume that residential gateways have a symmetric low-speed Internet connection with $C_r^d = 3.5$ Mbps and $C_r^u = 3.5$ Mbps.

The interference in the network is simulated using the Protocol Model, and the transmission range and interference range of each node are fixed and equal to 100m and 200m, respectively. Regarding the MAC protocol, we have implemented the collision-free CSMA-based access scheme described in Section 2. A more realistic MAC protocol, using practical collision avoidance mechanisms (e.g., 802.11-based backoff algorithm) will be considered in future work. The wireless channel bandwidth is fixed and set to $C_w = 50$ Mbps. Finally, the wireless channel is assumed noiseless.

Regarding the traffic model, in this study we use UDP as the transport protocol for generating data traffic. We consider Internet flows established between the wired infrastructure and randomly selected mesh nodes. Each flow is *bidirectional* because a mesh node can both download and upload traffic from/to the Internet. Following the notation introduced in Section 4, the $b_u^{(k)}$ and $b_d^{(k)}$ parameters are the average uplink and downlink bandwidth, respectively, demanded by each flow $f^{(k)}$. If not otherwise specified, in the following tests both $b_u^{(k)}$ and $b_d^{(k)}$ are random values uniformly selected in the range [50kbps, 150kbps], while the inter-packet arrival time is exponentially distributed.

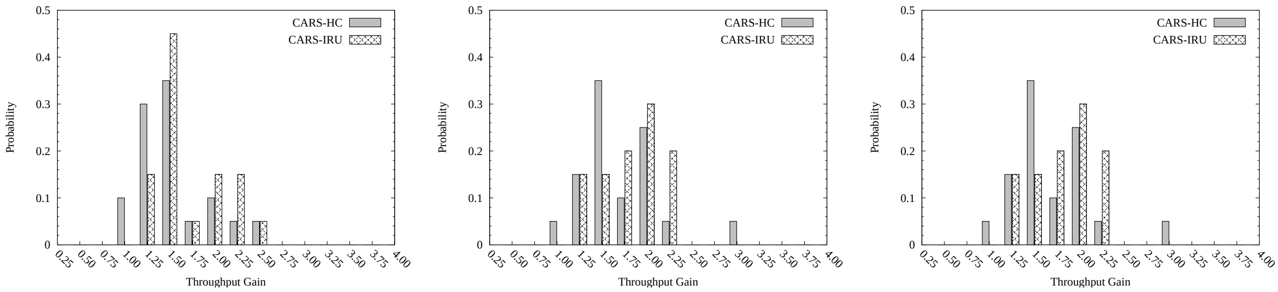
5.2 Model Validation

In this section we validate the accuracy of the developed analysis by comparing the network capacity predicted using our model, and the network capacity measured through



(a) $n_r/n = 0.05$ (b) $n_r/n = 0.1$ (c) $n_r/n = 0.2$

Figure 3: Comparison between predicted and measured network capacity for symmetric Internet flows ($b_u^{(k)} = b_d^{(k)}, \forall f^{(k)}$).



(a) $n_r/n = 0.05$ (b) $n_r/n = 0.1$ (c) $n_r/n = 0.2$

Figure 4: Histogram of throughput gains of *CARS-HC* and *CARS-IRU* over *SPF-IRU* for symmetric Internet flows (i.e., $b_u^{(k)} = b_d^{(k)}, \forall f^{(k)}$).

simulations in different network scenarios. Following Definition 2, to compute the network capacity we use randomly generated traffic traces. More precisely, each flow of the traffic trace is sequentially injected into the network, and the maximum network capacity is obtained when a new flow cannot be accepted without saturating one of the queues in the network.

In the following, we investigate diverse levels of network heterogeneity by varying the percentage of residential gateways over mesh routers. Due to space limitations, we report only plots related to the *SPF-IRU* scheme, but similar results have been also obtained with hop count metric and with CARS algorithm. For the sake of clarity, we present a brief description of IRU definition as reported in [25]. Specifically, to capture inter-flow interference, the IRU metric for link l is defined $IRU_l = ETT_l \times N_l$, where N_l denotes the number of mesh nodes with which the transmission on link l interferences, while ETT_l [10] is the expected transmission time on link l. Hence, the IRU cost captures the aggregated channel time that transmissions on link l consume on neighboring nodes, which essentially represents the inter-flow interference.

Figures 3 show a set of scatter plots comparing the network capacity predicted by our model and the one measured through simulations for symmetric Internet flows (i.e., $b_u^{(k)} = b_d^{(k)}, \forall f^{(k)}$), and for different numbers of residential gateways in the mesh network. Each network scenario consists of twenty topologies, and each topology instance is averaged over five different traffic traces[4]. The plots show that the correspondence between theory and simulation is good in all the considered scenarios. Moreover, the numerical results indicate that the network capacity is greatly dependent on the specific mesh topology and locations of residential gateways. This motivates the CARS design principle of jointly considering locations of gateways and traffic flow patterns during the route selection process.

5.3 CARS Performance

Different variants of the CARS scheme can be devised depending on the cost function used to compute the optimal set of network paths between the mesh nodes and the available gateways. The simplest solution is to use the hop count metric, which is completely topology- and traffic-independent. Using hop count metric allows us to isolate the impact on system performance of gateway selection from intra-mesh routing. Another natural option is to construct the set of optimal network paths using the IRU metric. For brevity, we refer to the first solution as *CARS-HC*, and to the latter as *CARS-IRU*.

We evaluate the efficiency of *CARS-HC* and *CARS-IRU* schemes in terms of their *throughput gain* G, i.e., the ratio between the maximum network capacity they obtain and the one achieved by *SPF-IRU* routing algorithm. Since network capacity measurements have a high dispersion over different topologies, rather than using mean or standard deviation as comparison metric, we analyze the *probability distribution* of throughput gains, which provides a deeper insight on system behaviors. To this end, Figures 4 show the normalized frequency of throughout gains for the same topologies and parameter settings considered in Figures 3. Note that

[4]Confidence intervals are very tight and are not reported.

the specific shape of the histograms depends on the set of 20 topologies we used during both analysis and simulations. It is intuitive to realize that different sets would generate different pdfs. More precisely, let us denote with g_i the i-th value of throughput gain reported on the x axis of Figures 4 (e.g., $g_i = 1.5$ for $i = 6$). Then, the height of the bar centered on g_i provides the probability that the throughput gain measured in the tested topologies fall in the range $[g_{i-1}, g_i]$.

The plotted curves show that both CARS variants ensure an overall throughput improvement over *SPF-IRU* between 25% and 100% in most of the considered topologies. However, there are a few topologies where *CARS-HC* performs worse (around 20%) than *SPF-IRU* algorithm. This occurs for particularly disadvantaged topologies where almost all residential gateways happened to be close to each other. In these conditions, hop count metric is particularly inefficient because it leads to select close paths, and even an optimized gateway selection cannot mitigate this inefficiency. On the contrary, *CARS-IRU* always outperforms *SPF-IRU*. This is an expected results because *CARS-IRU* scheme performs route selection on the same set of paths computed by *SPF-IRU* algorithm, but it is not restricted to select the path to the "closest" gateway if this is saturated. However, there are also topologies where *CARS-HC* obtain throughput improvements around 200%, and even higher than *CARS-IRU* scheme. Nevertheless, *CARS-IRU* shows better average performance than *CARS-HC*. Thus, the shown results confirm that CARS ensures a more efficient utilization network resources (both wireless and wired) than *SPF-IRU*, but they also highlight the tight interaction between route selection and gateway selection.

6. CONCLUSIONS

In this paper we have shown that a multi-class queuing network model can be effectively used to model the network capacity of heterogeneous WMNs, and to identify network bottlenecks. Moreover, we have proposed CARS, a capacity-aware routing selection algorithm that takes advantage of model predictions to evenly distribute the network load among available gateways. We have shown through simulations that CARS significantly outperforms shortest path routing algorithms using link costs that capture only inter-flow interference.

In this study we have used an idealized CSMA-based MAC protocol, which primarily captures location-dependent contention issues due to differences in the number of contending nodes at both endpoints of each communication link. The extension of our analysis to a MAC protocol implementing practical collision avoidance mechanisms, is a challenge that needs to be addressed. Furthermore, a more comprehensive investigation of the impact of traffic asymmetry and fixed lines capacities on network performance of heterogeneous WMNs is also an ongoing activity.

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